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ORIGINAL RESEARCH

Why does stock-market investor sentiment influence corporate investment?

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Abstract

We examine the relationship between corporate investment and investor sentiment at the firm level with the predicted change in investor sentiment. Empirically, we find that there is a large predictable mean reversion component in investor sentiment, and that a predicted increase in investor sentiment, capturing an unwinding of past market sentiment, positively affects the investment and debt issuance of firms with lower credit ratings, but not their equity issuance. Our results suggest that the positive relationship between investor sentiment and corporate investment may be due to that corporate managers are also driven by investor sentiment.

Keywords Stock-Market Investor Sentiment · Corporate investment · Net equity issuance · Net debt issuance

JEL classification G02 · G31 · G32

> In abnormal times in particular… the market will be subject to waves of optimistic and pessimistic sentiment, which are unreasoning and yet in a sense legit-

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imate where no solid basis exists for a reasonable calculation. – The General Theory of Employment, Interest, and Money, John Maynard Keynes (1936).

1 Introduction

Corporate investment is important to understand business cycles (Justiniano et al. 2010). Since Keynes (1936), economists have speculated that stock-market investor sentiment may be an important driver of corporate investment and business cycles. For instance, the model of Benhabib et al. (2015) suggests that market sentiment can affect the equilibrium output, as imperfect information is used in forecasting both demand in production decisions and income in household decisions. Milani (2017) defines sentiment as the deviations of observed expectations from their levels explained by a near-rational learning model. His sentiment measure captures waves of excessive optimism and pessimism and can be very persistent. Including 'sentiment' in a dynamic stochastic general equilibrium model of the U.S. economy, Milani (2017) show that sentiment shocks have significant impact on business cycle fluctuations, particularly on expectations related to future investment decisions. Empirically, Arif and Lee (2014) find that aggregate investment is positively correlated with stock-market investor sentiment, and that higher aggregate investment precedes lower corporate earnings and lower GDP growth. Arif and Lee (2014) conclude that their findings "point to the possibility that corporate managers are influenced by the same waves of optimism (or pessimism) as other investors." (p. 8) Jiang et al. (2019) construct a manager sentiment index based on the aggregated textual tone of corporate financial disclosures, and find that higher manager sentiment precedes lower aggregate earnings surprises and greater aggregate investment growth.

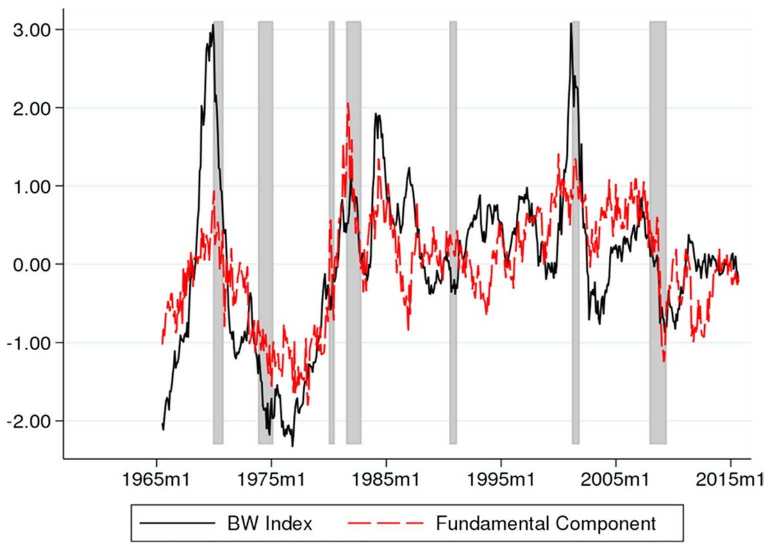

Fig. 1 Baker and Wurgler (BW) sentiment index. The solid line shows the time series of Baker and Wurgler (2006) sentiment index. The shaded areas indicate the NBER-dated U.S. recessions. The data spans from July 1965 to September 2015.

In this paper, we investigate the impact on corporate investment of the *predicted* change in stock-market investor sentiment, as opposed to the *actual* change in investor sentiment. As Arif and Lee (2014) imply, the correlation between actual investor sentiment and corporate investment could be due to confounding factors. Figure 1 depicts the orthogonalized stock-market investor sentiment index of Baker and Wurgler (2006) (BW Index), which is used by Arif and Lee (2014), with the shaded areas indicating the NBER-dated U.S. recessions. Although by construction the BW index is orthogonal to common macroeconomic variables, it is still evidently procyclical in that the BW index typically rises in expansions and decreases in recessions. Along this line, Sibley et al. (2016) find that the BW index can be largely explained by fundamental variables. They also show that the predictive ability of the BW index in the cross section of stock returns is mainly driven by the component of the BW index that is related to fundamental variables. Thus, the positive correlation between actual investor sentiment and corporate investment in previous research (e.g., Arif and Lee 2014) could be due to fundamental-related confounding factors, not investor sentiment. To investigate the causal impact of stock-market investor sentiment on corporate investment, in the same spirit of López-Salido et al. (2017), we use the predicted change in investor sentiment instead of the actual change, because the former captures an unwinding of past investor sentiment and is less likely driven by fundamental-related confounding factors.

Furthermore, different from previous studies (e.g., Arif and Lee 2014; Jiang et al. 2019), we examine not only corporate investment but also financing activities, because financing decisions can help test alternative explanations for the investment-sentiment relationship. We focus on two alternative explanations. The first one is the "managerial catering" hypothesis in which corporate managers rationally time their equity issuance and investment to take advantage of behavioral biases of sentiment-driven stock investors. This hypothesis thus predicts a positive correlation between stock-market investor sentiment and equity issuance. The second explanation is the "manager bias" hypothesis in which corporate managers are also subject to investor sentiment and can overinvest when investor sentiment is high. Overly optimistic managers neglect risk and use debt to finance overinvestment. This hypothesis therefore implies a positive relationship between investor sentiment and debt issuance. It is important to point out that these two hypotheses are not mutually exclusive, as both investors and corporate managers could be driven by market sentiment.

Empirically, we first provide evidence that there is a predictable mean reversion component in stock-market investor sentiment measured by the BW index. High investor sentiment in year $t-2$ predicts a decrease in the sentiment in year t, with an adjusted R^2 of 0.269 for the sample period from 1967 to 2015. This finding is consistent with the common description of investor sentiment (i.e., "What goes up must come down"), and parallels the mean reversion of credit-market sentiment documented in López-Salido et al. (2017). Furthermore, we show that the predicted change in stock-market investor sentiment captures an unwinding of past investor sentiment and is less likely driven by fundamental-related confounding factors. For instance, we follow Sibley et al. (2016) to construct the component of the BW index that is related to fundamental variables, and find that the predicted change in the BW index is insignificantly correlated with this component when we exclude three outlier years.

Next, we use the predicted change in the BW index to investigate the causal impact of stock-market investor sentiment on corporate investment and to test the two alternative explanations for the sentiment-investment relationship (i.e., the "managerial catering" hypothesis and the "manager bias" hypothesis). Our findings can be easily summarized. A predicted increase in investor sentiment positively forecasts corporate investment and net debt issuance of firms with lower credit ratings, but has no significantly positive impact on the net equity issuance of those firms. Furthermore, high investment/debt issuance in year t predicts poor subsequent performance, particularly for firms with lower credit ratings. The evidence thus suggests that when stock-market investor sentiment is high, corporate managers become overly optimistic and overinvest through issuing debt. That is, stock-market investor sentiment does have a causal impact on corporate investment, and the "manager bias" hypothesis provides an economic explanation.[1]

Our paper contributes to the rapidly growing behavioral finance literature. Much of the research focuses on the effects of stock-market investor sentiment on equity returns. For instances, Baker and Wurgler (2006, 2007) develop the BW sentiment index and find that investor sentiment helps explain the cross section of equity returns. Baker et al. (2012) provide parallel international evidence. Stambaugh et al. (2012) show that investor sentiment helps explain a broad set of asset-pricing anomalies. Baker, Wurgler, and Yuan (2014) provide more supporting evidence based on simulations. Stambaugh and Yuan (2017) imply that investor sentiment can be a priced factor that captures common sources of mispricing.[2] Extending Arif and Lee (2014), we study the causal impact of stock-market investor sentiment on corporate investment, and test the alternative explanations by taking into account corporate financing activities. Our results suggest that stock-market investor sentiment, as speculated by Keynes (1936), could be a driver of corporate investment and business cycles, as corporate managers, particularly those in firms with lower credit ratings, are also subject to investor sentiment and can over- or under-invest when investor sentiment is high or low.

Our paper is also related to the literature on leverage and financial crises. Previous research (e.g., Schularick and Taylor, 2012; Baron and Xiong, 2017; Fahlenbrach et al. 2018) finds that bank-loan growth predicts poor economic performance and financial crises. Extending this literature, we provide evidence that debt issuance in the credit market is also driven by sentiment and predicts subsequent performance of firms, particularly for firms with lower credit ratings.

The remainder of the paper is organized as follows: Sect. 2 develops our hypotheses; Sect. 3 tests if there is a predictable reversal in stock-market investor sentiment; Sect. 4 examines the impact of the predicted change in stock-market investor sentiment on corporate investment and financing activities; Sect. 5 concludes the paper with a brief summary.

2 Hypotheses

Applying a time-series approach, Arif and Lee (2014) examine the relationship between aggregate investment, stock-market investment sentiment, and future stock market returns. Aggregating net operating investment over publicly traded firms, Arif and Lee (2014) find that aggregate investment is highly procyclical (i.e., it increases in economic expansions and deceases in recessions), and that aggregate investment is positively correlated with the BW index. As we have pointed out, the positive correlation between the BW index and corporate investment could be due to fundamental-related confounding factors. Therefore, to

[1] Our finding is consistent with previous studies on the role of managerial traits in explaining firms' financing decisions See, for instance, Malmendier et al. (2011), Graham et al. (2013), and Ben-David et al. (2013).

[2] See also Balvers and Wu (2000, 2006), Chen and Kuo (2014), Szu et al. (2015), Baek (2016), Du and Zhao (2017), Ding et al. (2018), and Du and Hu (2018).

investigate the causal impact of stock-market investor sentiment on corporate investment, we use the predicted change in the BW index based on lagged sentiment measures, as opposed to the actual change in the BW index. We discuss how we construct the predicted change in the BW index in Sect. 3.1.

Furthermore, we employ firm-level analysis, not aggregate-level analysis as in Arif and Lee (2014) and Jiang et al. (2019), to help shed more empirical light. Intuitively, if investor sentiment simply proxies the effects of fundamental-related confounding factors, it should affect investment of all firms, because economic fundamentals matter for all firms. However, if investor sentiment has causal effects on corporate investment due to behavioral biases of investors and/or corporate managers, it should primarily affect firms with lower credit ratings. First, firms with lower credit ratings tend to be financially distressed, more speculative, and harder to arbitrage,[3] making their stock prices more likely driven by investor sentiment. If (rational) corporate managers time their equity issuance and investment to take advantage of behavioral biases of stock investors, stock-market investor sentiment can causally drive corporate investment, particularly for firms with lower credit ratings. Second, firms with lower credit ratings are also unlikely to attract and hire high quality (i.e., rational) managers. If corporate managers are also subject to investor sentiment and overinvest when investor sentiment is high, stock-market investor sentiment can causally influence corporate investment, again particularly for firms with lower credit ratings. Therefore, our first hypothesis is:

Hypothesis 1 Stock-market investor sentiment causally impacts corporate investment, particularly for firms with lower credit ratings.

As we have implied, there are two alternative explanations for the sentiment-investment relationship. One explanation is the "managerial catering" hypothesis in which corporate managers rationally time their stock issuances and investment to take advantage of investor behavioral biases.[4] There is some evidence in the behavioral finance literature that is supportive of this hypothesis. For instance, Baker et al. (2003) find that non-fundamental stock price movement and subsequent corporate investment are positively correlated, and that the correlation is particularly pronounced for equity-dependent firms (those that are young, or have high leverage, low cash balance, or low cash flows).[5] Using fire sales to identify truly exogenous underpricing, Hau and Lai (2013) find that stock underpricing negatively affects corporate investment and employment, particularly for the financially constrained firms. Employing a forward-looking measure of equity fundamental value to identify mispricing, Dong et al. (2012) find that equity issuance and total financing increase with equity overvaluation. Furthermore, the sensitivity of equity issuance to mispricing is stronger among firms with high growth opportunities (small size, low book-to-market ratio, and high level of R&D). Campello and

[3] For instance, as Baker and Wurgler (2007) point out, "A natural proxy for speculative appeal would be the dispersion of professional analysts' earnings forecasts for that company" (p. 144). Avramov et al. (2009) find that firms with lower credit ratings often have higher forecast dispersion.

[4] See for instance Asquith and Mullins (1983), Korajczyk et al. (1991), Loughran and Ritter (1997), Baker and Wurgler (2002), and Huang and Ritter (2009).

[5] Baker et al. (2003) also find that equity-dependent firms with high investment tend to have low subsequent stock returns and high volume of equity issuance. See also Dittmar and Thakor (2007), Baker et al. (2009), and Chirinko and Schaller (2011).

Graham (2013) examine the cross-sector spillover effect of mispricing from tech sector to non-tech manufacturers during the 1990s technology bubble, and find that the non-fundamental price run-up of tech sector has a positive and significant impact on the capital spending of financially constrained non-tech firms. Moreover, to identify the mechanism through which mispricing affects corporate investment, Campello and Graham (2013) demonstrate that constrained non-tech firms issue more shares in response to mispricing than what is suggested by investment opportunities.[6] It is important to point out that although the aforementioned papers attempt to gauge the impact of mispricing in the stock market on corporate investment and financing decisions, they do not directly examine the impact of stock-market investor sentiment. We hypothesize that if managers rationally time their stock issuances and investment to take advantage of sentiment-driven mispricing, there should be a positive correlation between stock-market investor sentiment and equity issuance, particularly for firms with lower credit ratings, as stock prices of these firms are more likely affected by investor sentiment. Hence, our second hypothesis (i.e., the "managerial catering" hypothesis) is:

Hypothesis 2 The "managerial catering" hypothesis predicts that there should be a positive correlation between stock-market investor sentiment and equity issuance, particularly for firms with lower credit ratings.

Alternatively, if corporate managers are themselves subject to investor sentiment, they would tend to bias their evaluation of investment opportunities. For instance, driven by stock-market investor sentiment, an overly optimistic manager would likely overestimate future cash flows and/or underestimate the risk of new investment projects. Since new equity issuance is more expensive (e.g., Myers 1984; Fama and French 2002), overly optimistic corporate managers may neglect risk and use debt issuance. Consequently, there would be a positive relationship between investor sentiment and debt financing. Furthermore, such a positive relationship should be particularly strong for firms with lower credit ratings, as such firms are unlikely to attract and hire high quality (i.e., rational) managers. Therefore, our third hypothesis (the "manager bias" hypothesis) is:

Hypothesis 3 The "manager bias" hypothesis predicts that there should be a positive relationship between investor sentiment and debt issuance, particularly for firms with low credit ratings.

3 Predicted change in stock-market investor sentiment

Given that stock-market investor sentiment is in part driven by fundamental variables, the positive correlation between investor sentiment and corporate investment documented in Arif and Lee (2014) could be due to fundamental-related confounding factors. Inspired by López-Salido et al. (2017), we use the predicted change in investor

[6] In addition, Campello and Graham (2013) find that constrained non-tech firms tend to save more cash from equity issuance than tech bubble firms. See also Almeida et al. (2004), Bolton et al. (2013), and Chen et al. (2019). See Caballero et al. (2006) and Jermann and Quadrini (2012) for theory.

sentiment to investigate the causal impact of investor sentiment on corporate investment. In this section, we discuss how we construct the predicted change in investor sentiment based on lagged sentiment measures, and show that this predicted change is less likely driven by fundamental-related variables,

3.1 Reversal in stock-market investor sentiment

Following the sentiment literature (e.g., Arif and Lee 2014; Chen et al. 2019), we use the orthogonalized Baker and Wurgler (2006) sentiment index (BW index) from Professor Jeffrey Wurgler's website.[7] The BW index (as of March 2019) is available for the period from July 1965 to September 2015. To focus on the business-cycle frequency sentiment fluctuations, we collapse monthly data to annual frequency by taking the year-end sentiment value for each calendar year. To test if there is a predictable reversal in the BW index, in the same spirit of López-Salido et al. (2017), we estimate the following benchmark model:

$$\Delta s_t = a + b_1 s_{t-2} + b_2 \log PE10_{t-2} + e_t \tag{1}$$

where Δs_t is the change in the BW index in year t, s_{t-2} is the BW index in year $t-2$, and $PE10_{t-2}$ is the cyclically adjusted P/E ratio for the S&P 500 (Shiller 2000) from Professor Shiller's website. Both s_{t-2} and $\log PE10_{t-2}$ help capture the stock-market investor sentiment in year $t-2$. If "what goes up must come down", we expect the coefficients on s_{t-2} and $\log PE10_{t-2}$ to be negative.

The regression results are reported in Table 1. Heteroscedasticity- and autocorrelation-consistent standard errors are computed according to Newey and West (1987) with the automatic lag selection method of Newey and West (1994). Column (1) shows the benchmark regression over the sample period from 1967 to 2015 (we lose 1965 and 1966 because we employ the two-year lagged BW index and the BW index starts in 1965). The coefficients on s_{t-2} and $\log PE10_{t-2}$ are both negative, although only the coefficient on s_{t-2} is statistically significant. The adjusted-R^2 is 0.269, suggesting that the lagged sentiment measures in year $t-2$ have economically significant power to predict the BW index change in year t. Overall, the evidence suggests that there is a predictable reversal component in the BW index. This finding parallels the mean reversion of credit-market sentiment documented in López-Salido et al. (2017) and Du (2017).

One concern is that our results may be driven by a small number of disproportionately influential observations. We investigate this issue more formally with the partial regression plots (i.e., the added variable plots) in Fig. 2. Specifically, to construct the partial regression plot for s_{t-2}, we first compute the residuals of regressing Δs_t against $\log PE10_{t-2}$, then estimate the residuals of regressing s_{t-2} against $\log PE10_{t-2}$, and finally plot the residuals from the first regression against those from the second regression in Panel A of Fig. 2. We repeat the similar analysis for $\log PE10_{t-2}$ and depict the plot in Panel B of Fig. 2. A few observations seem to stand out, namely 1968, 1970, and 2000. This is not surprising, as they correspond to the most dramatic movements in the BW index in Fig. 1. We therefore rerun our regression, except that we exclude the observations of 1968, 1970, and 2000. The results are in Column (2). As we can see, our results are qualitatively similar, although both s_{t-2} and $\log PE10_{t-2}$ become statistically significant.

[7] http://people.stern.nyu.edu/jwurgler/.

Table 1 Reversal in investor sentiment

	1967–2015		1985–2015		1967–2015	
	(1)	(2)	(3)	(4)	(5)	(6)
s_{t-2}	−0.439*** (−2.75)	−0.285*** (−3.47)	−0.535*** (−4.95)	−0.449*** (−12.58)	−0.551*** (−4.67)	−0.368*** (−6.26)
$\log PE10_{t-2}$	−0.020 (−0.09)	−0.257* (−1.86)	−0.122 (−0.91)	−0.410*** (−2.81)	−0.287* (−1.73)	−0.423*** (−3.05)
cs_{t-2}					0.043 (0.66)	0.013 (0.23)
$\log HYS_{t-2}$					0.238*** (2.86)	0.151** (2.47)
Observations	49	46	31	30	49	46
Adj-R^2	0.269	0.249	0.214	0.302	0.318	0.269

We estimate the following benchmark model: $\Delta s_t = a + b_1 s_{t-2} + b_2 \log PE10_{t-2} + e_t$ where Δs_t is the change in the BW index in year t, s_{t-2} is the BW index in year $t-2$, and $PE10_{t-2}$ is the cyclically adjusted P/E ratio for the S&P 500 (Shiller 2000) from Professor Shiller's website. We also explore to include the bond-market sentiment measures, namely the level of the credit spread at the end of year $t-2$ (cs_{t-2}) and the log of the high-yield bond issuance in year t−2 ($\log HYS_{t-2}$). The credit spread is defined as the spread between yields on corporate BAA bonds and yields on 10-year Treasury securities from the Federal Reserve Economic Data (FRED). The high-yield bond issuance is expressed as a percentage of total bond issuance in the nonfinancial corporate sector from Greenwood and Hanson (2013). Heteroscedasticity- and autocorrelation-consistent standard errors are computed according to Newey and West (1987) with the automatic lag selection method of Newey and West (1994)

***$p<0.01$, **$p<0.05$, *$p<0.1$

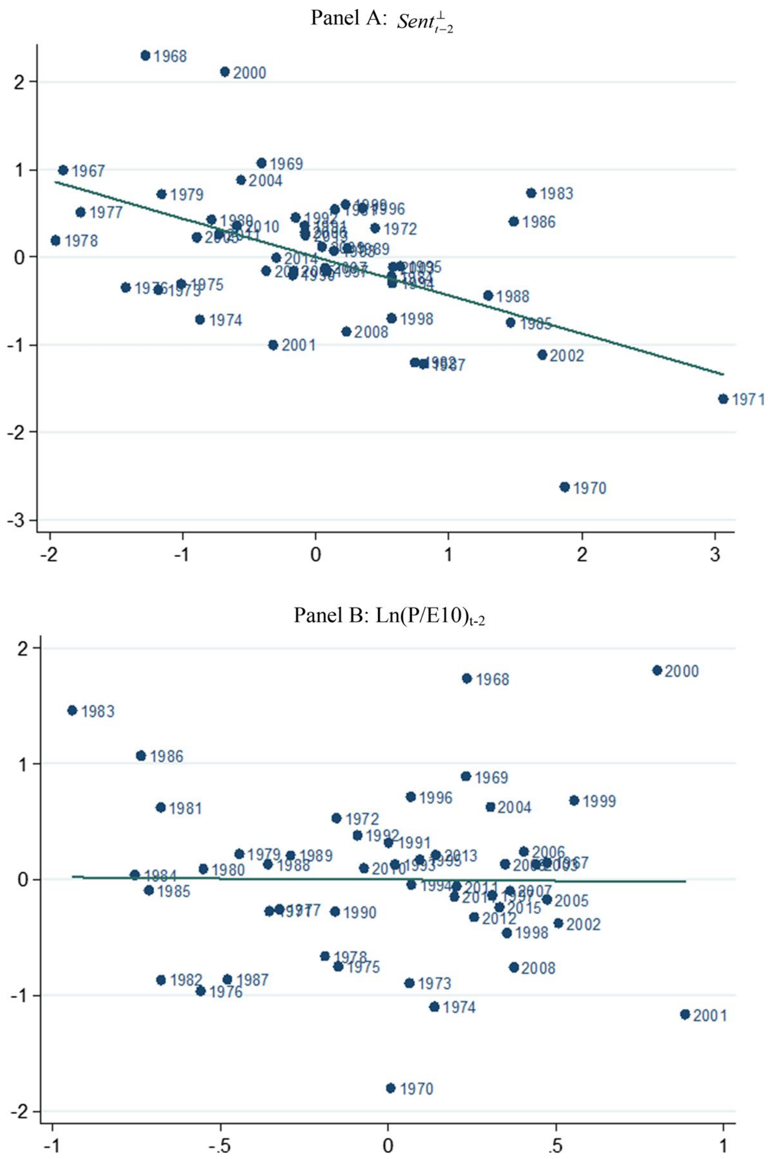

Fig. 2 Partial regression plot for influential data points. To construct the partial regression plot for s_{t-2}, we first compute the residuals of regressing Δs_t against ln(P/E10)$_{t-2}$,then estimate the residuals of regressing s_{t-2} against ln(P/E10)$_{t-2}$, and finally plot the residuals from the firstregression against those from the second regression in Panel A. We repeat the similar analysis for ln(P/E10)$_{t-2}$ anddepict the plot in Panel B

Next, we examine a more recent sample period of 1985–2015. The purpose is to match the sample period for the firm-level regressions in the next section. The results are presented in Columns (3) and (4). In Column (3), we include all sample years. As we can see, the results are similar as those based on the longer sample of 1967–2015. For instance, the coefficients on s_{t-2} and log $PE10_{t-2}$ are both negative, although only the coefficient on s_{t-2}

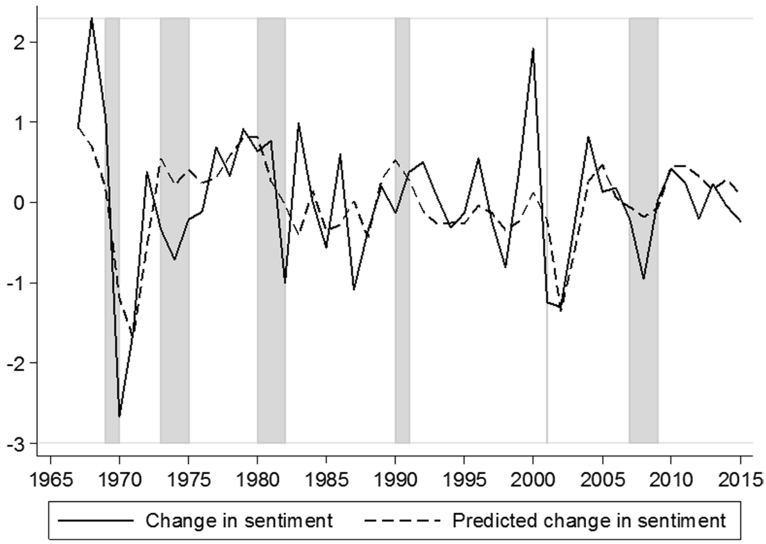

Fig. 3 Actual changes and predicted changes in investor sentiment. This figure depicts the changes in investor sentiment (i.e., Δst) as well as the predicted change in investor sentiment (i.e., $\Delta\hat{s}_t = \hat{b}_1 s_{t-2} + \hat{b}_2 In(P/E10)_{t-2} + \hat{b}_3 InHYS_{t-2}$). The shaded areas indicate the NBER-dated U.S. recessions

is statistically significant. In Column (4), we exclude the outlier year of 2000. Interestingly, both s_{t-2} and $\log PE10_{t-2}$ become strongly significant.

We also explore to include the bond-market sentiment measures used by López-Salido, Stein, and Zakrajšek (2017), namely the level of the credit spread at the end of year $t-2$ (cs_{t-2}) and the log of the high-yield bond issuance in year t−2 ($\log HYS_{t-2}$). The credit spread is defined as the spread between yields on corporate BAA bonds and yields on 10-year Treasury securities from the Federal Reserve Economic Data (FRED). The high-yield bond issuance is expressed as a percentage of total bond issuance in the nonfinancial corporate sector from Greenwood and Hanson (2013).[8] The results are presented in Columns (5) and (6). In Column (5), we include all sample years from 1967 to 2015. First, s_{t-2} and $\log PE10_{t-2}$ enter with statistically significantly negative coefficients, implying a reversal in the stock-market investor sentiment. Second, $\log HYS_{t-2}$ enters with a significantly positive coefficient, suggesting that a low level of the high-yield bond issuance in year $t-2$ (i.e., low credit-market sentiment) predicts a subsequent decrease in the BW index (which captures the stock-market sentiment) in year t. This may reflect the substitutability between stocks and bonds. That is, low credit-market sentiment in year $t-2$ may be consistent with high stock-market sentiment, which would reverse. In Column (6), we exclude the outlier years of 1968, 1970, and 2000. As we can see, our results are qualitatively unchanged in that $\log HYS_{t-2}$ still enters with a significantly positive coefficient, suggesting that it may have marginal predictive power. Therefore, in the next section, we use s_{t-2}, $\log PE10_{t-2}$ and $\log HYS_{t-2}$ to predict Δs_t. Figure 3 depicts the changes in investor sentiment (i.e., Δs_t.) as well as the predicted change in investor sentiment (i.e., $\Delta\hat{s}_t = \hat{a} + \hat{b}_1 s_{t-2} + \hat{b}_2 \log PE10_{t-2} + \hat{b}_3 \log HYS_{t-2}$). As we can see, the unwinding of past stock-market investor sentiment (i.e., $\Delta\hat{s}_t$) drives substantial movements in investor

[8] https://www.hbs.edu/faculty/initiatives/behavioral-finance-and-financial-stability/Pages/sentiment.aspx.

sentiment, which makes it ideal to test the causal effects of investor sentiment on corporate investment. For robustness, we also report the results based on only the benchmark sentiment predictors (i.e., s_{t-2} and log $PE10_{t-2}$).

3.2 Actual versus predicted changes in the BW index

One major difference between this paper and previous studies (e.g., Arif and Lee 2014; Chen et al. 2019) is that we use the predicted, not actual, change in the BW index. While the actual change in the BW index is dependent on fundamental-related variables (Sibley et al. 2016), the predicted change in the BW index based on Eq. (1) is in principle less likely driven by fundamental variables, as it is constructed from the predictable mean reversion in the BW index. In this section, we provide empirical evidence to support this conjecture.

Specifically, we follow Sibley et al. (2016) and take into account 13 fundamental variables. There are six macroeconomic variables: the U.S. unemployment rate (Unemp) as in Lemmon and Portniaguina (2006); the CPI inflation (dCPI) as in Chen et al. (1986); the consumption growth rate (dCons) as in Chen et al. (1986); the growth rate of disposable personal income (dSPI) as in Lemmon and Portniaguina (2006); the growth rate of industrial production (dInd) as in Chen et al. (1986); and the NBER recession dummy (NBER) as in Baker and Wurgler (2006). There are four financial variables that are often used to capture the business cycle: the 3-month Treasury Bill rate (Tbill) as in Hodrick (1992); the default spread (Def), defined as the difference in yields between Baa-rated corporate bonds and AAA-rated corporate bonds, as in Chen et al. (1986); the term spread (Term), defined as the difference in yields between the 10-year Treasury bond and the 3-month T-bill, as in Chen et al. (1986); the dividend yield (Div) as in Campbell and Shiller (1988). There are also three risk factors: the return on the value-weighted CRSP market index (VWRETD) as in Sharpe (1964); the stock market volatility (MktVol), computed as the annualized standard deviation of market daily return within each month, as in Bollerslev et al. (2009); and the liquidity risk factor proposed by Lee (2011), defined as the market average of firm level percentage of zero return days (PctZero).

We collect monthly macroeconomic variables and yields data from FRED, and construct the monthly stock market volatility and liquidity with the CRSP data. Panel A of Table 2 shows the summary statistics of the 13 fundamental-related variables over our sample period from 1965 to 2015, which are very similar to those reported in Sibley et al. (2016) for a slightly shorter sample period from 1965 to 2010. In Panel B of Table 2, following Sibley et al. (2016), we regress the monthly BW index on the 13 fundamental variables over our sample period. Consistent with Sibley et al. (2016), the fundamental variables help explain substantial variation in the BW index. For instance, the adjusted-R^2 of the regression is 0.451, with eight out of 13 fundamental-related variables having statistically significant coefficients. We then construct the fundamental-component of the BW index based on the parameter estimates in Panel B of Table 2, and plot this component, "Fundamental Component", in Fig. 1 with the BW index. Not surprisingly, the fundamental-component of the BW index fluctuates with the BW index and is strongly procyclical. For instance, it rises prior to the global financial crisis of 2007–2009 and decreases sharply in the crisis.

Since we focus on business-cycle frequency fluctuations in investor sentiment in this paper, we collapse the monthly fundamental-component of the BW index to annual frequency by taking the year-end value for each calendar year, To test if the predicted

Table 2 Fundamental-related variables and investor sentiment

Panel A: Summary statistics of fundamental related variables

	Unemp	DCPI	DCons	dSPI	dInd	NBER
Mean	6.15	0.33	0.56	0.55	0.19	0.15
StdDev	1.65	0.32	0.54	0.75	0.74	0.36

	Tbill	Def	Term	Div	VWRETD	MktVol	PctZero
Mean	4.98	1.06	1.61	2.99	0.87	10.39	0.17
StdDev	3.23	0.45	1.28	1.19	4.50	6.15	0.11

Panel B: Decomposition regression

	Coefficient	t-stat
Unemp	−0.081	(−0.79)
dCPI	−0.349*	(−1.93)
dCons	−0.090*	(−1.94)
dSPI	−0.037	(−1.45)
dInd	−0.136**	(−2.56)
NBER	0.128	(0.48)
Tbill	0.420***	(6.18)
Def	−0.270	(−1.01)
Term	0.471***	(4.13)
Div	−0.336*	(−1.74)
VWRETD	−0.011	(−1.53)
MktVol	−0.016*	(−1.68)
PctZero	−7.135***	(−2.81)
Constant	0.544	(1.07)
Observations	603	
Adj-R^2	0.451	

We take into account 13 fundamental-related variables. There are six macroeconomic variables: the U.S. unemployment rate (Unemp); the CPI inflation (dCPI); the consumption growth rate (dCons); the growth rate of disposable personal income (dSPI); the growth rate of industrial production (dInd); and the NBER recession dummy (NBER). There are four financial variables that are often used to capture the business cycle: the 3-month Treasury Bill rate (Tbill); the default spread (Def), defined as the difference in yields between Baa-rated corporate bonds and AAA-rated corporate bonds; the term spread (Term), defined as the difference in yields between the 10-year Treasury bond and the 3-month T-bill; the dividend yield (Div). There are also three risk factors: the return on the value-weighted CRSP market index (VWRETD); the stock market volatility (MktVol), computed as the annualized standard deviation of market daily return within each month; and the liquidity risk factor proposed by Lee (2011), defined as the market average of firm level percentage of zero return days (PctZero). Panel A shows the summary statistics of the 13 fundamental-related variables over our sample period from 1965 to 2015. In Panel B, we regress the monthly BW index on the 13 fundamental-related variables over our sample period

Robust z-statistics in parentheses

***$p<0.01$, **$p<0.05$, *$p<0.1$

change in the BW index is less driven by fundamental variables, we regress the predicted change in the BW index based on Eq. (1), $\Delta\hat{s}_t = \hat{a} + \hat{b}_1 s_{t-2} + \hat{b}_2 \log PE10_{t-2}$, on the change in fundamental-component of the BW index ($\Delta s_t^{Fundamental}$). For comparison,

Table 3 Actual versus predicted changes in investor sentiment

	Δs_t	$\Delta \hat{s}_t$	$\Delta s_t^{Fundamental}$
Panel A: Summary statistics			
Mean	0.020	0.020	0.010
SD	0.852	0.467	0.610
p25	−0.315	−0.215	−0.380
p50	0.031	−0.004	−0.009
p75	0.500	0.297	0.422

	1967–2015		Exclude 1968, 1970 and 2000	
	(1)	(2)	(3)	(4)
	Δs_t	$\Delta \hat{s}_t$	Δs_t	$\Delta \hat{s}_t$
Panel B: Regression results				
$\Delta s_t^{Fundamental}$	0.546* (1.98)	0.157* (1.90)	0.351** (2.42)	0.078 (1.27)
Observations	49	49	46	46
Adj-R^2	0.135	0.022	0.076	−0.013

We construct the fundamental-component of the BW index based on the parameter estimates in Panel B of Table 2. To test if the predicted change in the BW index is less driven by fundamental-related variables, we regress the predicted change in the BW index based on Eq. (1), $\Delta \hat{s}_t = \hat{a} + \hat{b}_1 s_{t-2} + \hat{b}_2 \log PE10_{t-2}$, on the change in fundamental-component of the BW index ($\Delta s_t^{Fundamental}$). For comparison, we also regress the actual change in the BW index, Δs_t, on the change in its fundamental component. The results are reported in this Table. Heteroscedasticity- and autocorrelation-consistent standard errors are computed according to Newey and West (1987) with the automatic lag selection method of Newey and West (1994)

Robust z-statistics in parentheses

***$p<0.01$, **$p<0.05$, *$p<0.1$

we also regress the actual change in the BW index, Δs_t, on the change in its fundamental component. Panel A of Table 3 reports the summary statistics for the actual change in the BW index (Δs_t), the predicted change in the BW index ($\Delta \hat{s}_t$), and the change in the fundamental-component of the BW index ($\Delta s_t^{Fundamental}$). In Panel B, we present the regression results. Heteroscedasticity- and autocorrelation-consistent standard errors are computed according to Newey and West (1987) with the automatic lag selection method of Newey and West (1994). In Columns (1) and (2), we include all years from 1967 to 2015. As we can see, while the coefficient on $\Delta s_t^{Fundamental}$ is 0.546 in the Δs_t regression, it is only 0.157 in the $\Delta \hat{s}_t$ regression, a 70% reduction. In Columns (3) and (4), we exclude the three outlier years, namely 1968, 1970, and 2000. Interestingly, while the actual change in the BW index is still significantly correlated with the change in its fundamental component (with a coefficient of 0.351 and a robust t-statistic of 2.42), the predicted change in the BW index is not significantly correlated with $\Delta s_t^{Fundamental}$ (with a coefficient of 0.078 and a robust t-statistic of 1.27). The evidence thus supports our conjecture that the predicted change in the BW index based on Eq. (1) is less likely driven by fundamental-related variables.

4 Stock-market investor sentiment, corporate investment and financing activities

Section 3 shows that the predicted change in the BW index is less likely driven by fundamental variables. Therefore, in this section, we use the predicted change in the BW index to examine the causal effects of stock-market investor sentiment on corporate investment and financing activities. More specifically, we use firm-level data to test the three hypotheses we propose in Sect. 2.

4.1 Data and method

Hypothesis 1—Intuitively, if investor sentiment has causal effects on corporate investment, it should particularly affect firms with lower credit ratings, as stock prices of such firms may be more likely driven by investor sentiment and such firms are also unlikely to attract and hire high quality (i.e., rational) managers. To test this hypothesis, in the same spirit of López-Salido et al. (2017), we ask if the predicted change in investor sentiment (i.e., $\Delta \hat{s}_t = \hat{a} + \hat{b}_1 s_{t-2} + \hat{b}_2 \log PE10_{t-2} + \hat{b}_3 \log HYS_{t-2}$) has differential effects on corporate investment of firms with different credit ratings:

$$\begin{aligned} \Delta I_{i,t} = \beta_0 + \beta_1^{HY}\left(HY_{i,t-1} \times \Delta \hat{s}_t\right) + \beta_1^{LIG}\left(LIG_{i,t-1} \times \Delta \hat{s}_t\right) + \beta_1^{HIG}\left(HIG_{i,t-1} \times \Delta \hat{s}_t\right) \\ + \beta_2 \Delta cs_t + \beta_3 \Delta logY_{i,t} + \beta_4 \Delta \log Q_{i,t-1} + \mu_i + \varepsilon_{i,t} \end{aligned} \tag{2}$$

where $I_{i,t}$ is real business investment defined as nominal capital expenditures from Compustat deflated by the implicit price deflator for business fixed investment, $\Delta I_{i,t} = \log(I_{i,t}) - \log(I_{i,t-1})$, Δcs_t is the change in the credit spread, $Y_{i,t}$ is real sales defined as nominal sales from Compustat deflated by the implicit GDP deflator for the US nonfarm business sector, $Q_{i,t}$ is Tobin's Q, and μ_i is the firm fixed effect. Tobin's Q is defined as $\frac{V_{it}}{K_{it}^{phy}}$, where V_{it} is firm *i*'s market value in year *t* and K_{it}^{phy} is the book value of its tangible assets. HY, LIG, and HIG are indicators of the firm's credit quality.[9] López-Salido et al. (2017) use the firm rating data from the Moody's Default and Recovery Database (DRD). Because we do not have DRD, we use the long-term issuer credit ratings compiled by Standard & Poor's and reported on Compustat, which are also used in the finance literature (e.g. Avramov et al. 2009). These ratings reflect S&P's assessment of the creditworthiness of the obligor with respect to its senior debt obligations. Because the S&P rating data is very limited for the period prior to 1985, we restrict our empirical tests in this section to the post-1985 period. For all our firm-level panel regressions, we cluster standard errors by both firm and year to allow not only serial correlation within a firm but also spatial correlation across firms.

With Eq. (2), we allow the coefficients on $\Delta \hat{s}_t$ to differ across three credit-quality categories. We follow previous research (e.g., López-Salido et al. 2017) to include ΔlogY and ΔlogQ to control for firm-level fundamental-related determinants of corporate investment. We also account for the credit spread to control for aggregate economic and credit-market conditions. It is well known that credit spreads track business cycles (Fama and French

[9] HY (high yield) = BB+, BB−, BB, B+, B, B−, CCC+, CCC−, CCC, CC, C, D; LIG (low investment grade) = A, A+, A−, BBB, BBB+, BBB−; HIG (high investment grade) = AAA, AA+, AA, AA−.

Table 4 Summary statistics

	ΔNDI	ΔNEI	ΔI	Δlog Y	r	Δlog Q
High investment grade (HIG)						
Mean	0.44	−0.33	4.20	4.66	11.69	1.59
StdDev	5.76	3.91	24.58	10.90	22.01	27.36
Low investment grade (LIG)						
Mean	0.73	−0.26	4.56	5.27	8.79	0.34
StdDev	9.48	4.37	31.02	13.28	28.81	33.53
High yield (HY)						
Mean	0.88	−0.45	4.57	6.45	−0.45	−3.70
StdDev	13.46	5.13	41.57	16.64	54.30	39.11
All rated firms						
Mean	0.78	−0.35	4.54	5.75	4.91	−1.36
StdDev	11.23	4.69	35.72	14.74	42.01	35.80

Net debt issuance (NDI) is defined as long-term debt issuance minus long-term debt reduction, and $\Delta NDI_{i,t} = \frac{NDI_{i,t}-NDI_{i,t-1}}{AT_{i,t-1}}$ where $AT_{i,t-1}$ is the book value of total assets of firm i at the end of year $t-1$. Net equity issuance (NEI) is defined as sale of common and preferred stock minus purchase of common and preferred stock, and $\Delta NEI_{i,t} = \frac{NEI_{i,t}-NEI_{i,t-1}}{AT_{i,t-1}}$. I is real business investment which is defined as nominal capital expenditures deflated by the implicit price deflator for business fixed investment, and $\Delta I_{i,t} = \log(I_{i,t}) - \log(I_{i,t-1})$. $Y_{i,t}$ is real sales defined as nominal sales from Compustat deflated by the implicit GDP deflator for the US nonfarm business sector. $r_{i,t}$ is the total log return during firm i's fiscal year (we cumulate daily returns from CRSP over the firm's fiscal year). $Q_{i,t}$ is Tobin's Q of firm i. HY (high yield) = BB+, BB−, BB, B+, B, B−, CCC+, CCC−, CCC, CC, C, D; LIG (low investment grade) = A, A+, A−, BBB, BBB+, BBB−; HIG (high investment grade) = AAA, AA+, AA, AA−

1989), predict real economic activity (Gilchrist and Zakrajšek 2012) and bank credit losses (Du 2019), and explain average returns on stocks and bonds (Fama and French 1993).

Hypotheses 2 and 3—There may be two possible explanations for the sentiment-investment relationship. If managers rationally time their stock issuances and investment to take advantage of sentiment-driven mispricing, there should be a positive correlation between investor sentiment and equity issuance, particularly for firms with lower credit ratings, as stock prices of these firms are more likely impacted by investor sentiment (Hypothesis 2 or the "managerial catering" hypothesis). Alternatively, if corporate managers are themselves subject to investor sentiment, overly optimistic corporate managers may neglect risk and decide to use debt issuance to finance their overinvestment, resulting in a positive relationship between investor sentiment and debt issuance, particularly for firms with lower credit ratings, as such firms are unlikely to attract and hire high quality managers (Hypothesis 3 or the "manager bias" hypothesis). To test these hypothesis, in the same spirit of López-Salido et al. (2017), we estimate the following model:

$$\begin{aligned} \Delta F_{i,t} = \beta_0 + \beta_1^{HY}\left(HY_{i,t-1} \times \Delta\hat{s}_t\right) + \beta_1^{LIG}\left(LIG_{i,t-1} \times \Delta\hat{s}_t\right) + \beta_1^{HIG}\left(HIG_{i,t-1} \times \Delta\hat{s}_t\right) \\ + \beta_2\Delta cs_t + \beta_3\Delta logY_{i,t} + \beta_4 r_{i,t} + \mu_i + \varepsilon_{i,t} \end{aligned} \tag{3}$$

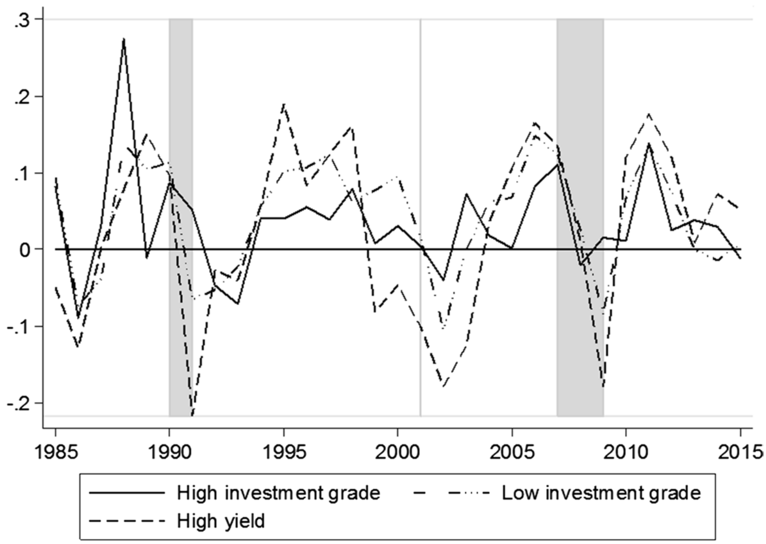

Fig. 4 Investment by credit rating. This figure plots the average growth rates of real capital expenditure of firms across three credit-rating categories. HY (high yield) = BB+, BB−, BB, B+, B, B−, CCC+, CCC−, CCC, CC, C, D; LIG (low investment grade) = A, A+, A−, BBB, BBB+, BBB−; HIG (high investment grade) = AAA, AA+, AA, AA−. The sample period is from 1985 to 2015. The shaded areas indicate the NBER-dated U.S. recessions

where $\Delta F_{i,t}$ is firm i's ΔNDI (change in net debt issuance) or ΔNEI (change in net equity issuance) in year t, and $r_{i,t}$ is the total log return during firm i's fiscal year (we cumulate daily returns from CRSP over the firm's fiscal year). Net debt issuance (NDI) is defined as long-term debt issuance minus long-term debt reduction from Compustat, and $\Delta NDI_{i,t} = \frac{NDI_{i,t} - NDI_{i,t-1}}{AT_{i,t-1}}$ where $AT_{i,t-1}$ is the book value of total assets of firm i at the end of year $t-1$. Net equity issuance (NEI) is defined as sale of common and preferred stock minus purchase of common and preferred stock from Compustat, and $\Delta NEI_{i,t} = \frac{NEI_{i,t} - NEI_{i,t-1}}{AT_{i,t-1}}$. Again, Δlog(Y) and Δcs are included to control for both firm- and aggregate-level fundamental-related determinants. Following López-Salido et al. (2017), we also account for $r_{i,t}$ to control for the effects of other relevant variables/events. For instance, a new patent may not increase the sales, but may increase both financing and investment as well as future cash flows. The stock return is forward looking and therefore helps control for this effect.

Because we need both stock prices and financial-statement data, we focus on the public firms in the CRSP-Compustat merged database. Following López-Salido et al. (2017), we exclude firms in the following NAICS sectors: Utilities, Postal Service, Finance and Insurance, Educational Services, Public Administration, and Unclassified. Furthermore, to mitigate the effects of outliers, we again follow López-Salido et al. (2017) and drop from the sample all firm/year observations where $\Delta NDI_{i,t}$, $\Delta NEI_{i,t}$, $\Delta I_{i,t}$, $\Delta log(Y_t)$, or $\Delta log(Q_t)$ is below the 2.5th or above the 97.5th percentile of its respective distribution.

Table 4 reports the summary statistics of the key variables used in the empirical tests. It shows that firms with lower credit ratings (i.e., HY and LIG firms) are more volatile, particularly in terms of their investment and debt financing activities. For instance, the standard deviations of ΔI are 41.57, 31.02, and 24.58% for HY, LIG, and HIG firms, respectively; the standard deviations of ΔNDI are 13.46, 9.48, and 5.76% for HY, LIG, and

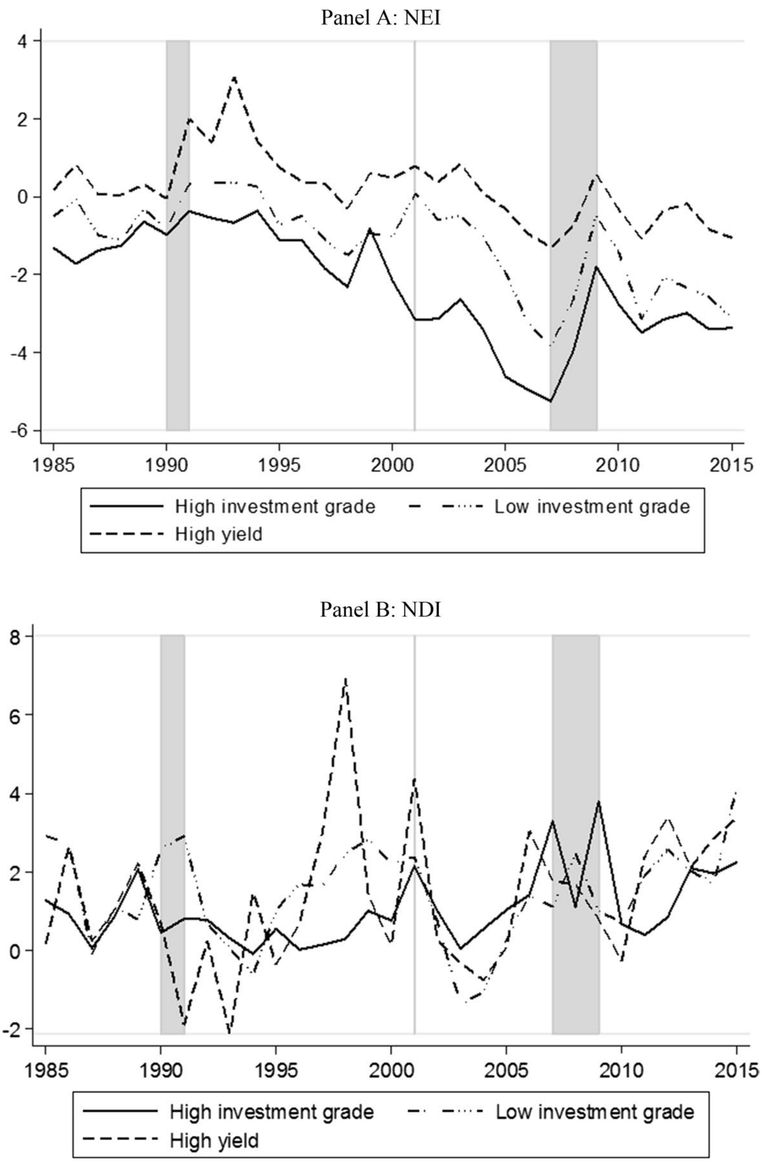

Fig. 5 Net debt and equity issuance by credit rating. Panel A depicts the average net equity issuance of firms across different credit ratings in our sample, and Panel B shows the average net debt issuance. HY (high yield) = BB+, BB−, BB, B+, B, B−, CCC+, CCC−, CCC, CC, C, D. The sample period is from 1985 to 2015. The shaded areas indicate the NBER-dated U.S. recessions

HIG firms, respectively. Figures 4 and 5 depict the time series of investment and financing activities over our sample period. Evidently, investment and financing activities of firms with lower credit ratings (i.e., HY and LIG firms) not only are more volatile but also have stronger business-cycle patterns. For instance, investment of high yield (HY) and low

Table 5 Predicted change in investor sentiment and investment by credit rating

	(1)	(2)	(3)	(4)	(5)
$HY_{i,t-1} \times \Delta\hat{s}_t$	8.64*** (3.32)	6.26*** (3.08)	6.32*** (3.07)	6.44*** (3.10)	8.10** (2.33)
$LIG_{i,t-1} \times \Delta\hat{s}_t$	6.94*** (3.33)	5.31*** (3.14)	5.34*** (3.11)	5.44*** (3.10)	6.56** (2.09)
$HIG_{i,t-1} \times \Delta\hat{s}_t$	− 0.32 (− 0.07)	− 1.06 (− 0.26)	− 1.07 (− 0.25)	− 1.20 (− 0.29)	− 1.67 (− 0.27)
$\Delta \log Y_{i,t}$		0.70*** (19.71)	0.70*** (20.63)	0.70*** (20.51)	0.70*** (20.35)
$\Delta \log Q_{i,t-1}$		0.17*** (10.43)	0.17*** (10.54)	0.17*** (10.59)	0.17*** (10.53)
Δcs_t			0.35 (0.53)	0.33 (0.50)	0.35 (0.52)
Firm FE	Yes	Yes	Yes	Yes	Yes
Industry FE	No	No	No	Yes	Yes
Observations	13,082	13,082	13,082	13,073	13,073
R^2_within	0.007	0.126	0.126	0.127	0.126
$P_{\mathrm{HY = HIG}}$	0.080	0.080	0.079	0.069	0.094
$P_{\mathrm{LIG = HIG}}$	0.062	0.067	0.067	0.056	0.086

We estimate the following model: $\Delta I_{i,t} = \beta_0 + \beta_1^{HY}(HY_{i,t-1} \times \Delta\hat{s}_t) + \beta_1^{LIG}(LIG_{i,t-1} \times \Delta\hat{s}_t) + \beta_1^{HIG}(HIG_{i,t-1} \times\Delta\hat{s}_t) + \beta_2\Delta cs_t + \beta_3\Delta \log Y_{i,t} + \beta_4\Delta \log Q_{i,t-1} + \mu_i + \varepsilon_{i,t}$

I is real business investment which is defined as nominal capital expenditures deflated by the implicit price deflator for business fixed investment, and $\Delta I_{i,t} = \log(I_{i,t}) - \log(I_{i,t-1})$. Δcs_t is the change in the credit spread defined as the spread between yields on corporate BAA bonds and yields on 10-year Treasury securities from the Federal Reserve Economic Data (FRED), $Y_{i,t}$ is real sales defined as nominal sales from Compustat deflated by the implicit GDP deflator for the US nonfarm business sector, $Q_{i,t}$ is Tobin's Q, μ_i is the firm fixed effect. HY, LIG, and HIG are indicators of the firm's credit quality. Sample period: annual data from 1985 to 2015. HY (high yield) = BB+, BB−, BB, B+, B, B−, CCC+, CCC−, CCC, CC, C, D; LIG (low investment grade) = A, A+, A−, BBB, BBB+, BBB−; HIG (high investment grade) = AAA, AA+, AA, AA−. For all our firm-level panel regressions, we cluster standard errors by both firm and year to allow not only serial correlation within firm but also spatial correlation across firms

***$p<0.01$, **$p<0.05$, *$p<0.1$

investment grade (LIG) firms rises and falls more sharply over business cycles, relative to that of high investment grade (HIG) firms.

4.2 Investor sentiment and corporate investment (Hypothesis 1)

If investor sentiment has causal effects on corporate investment, it should particularly affect firms with lower credit ratings. To test this hypothesis, we estimate Eq. (2) and report the results in Table 5.

In Column 1, we only account for the sentiment measures. Interestingly, there is only a positive correlation between the predicted change in investor sentiment and corporate investment for high-yield (HY) and low-investment-grade (LIG) firms (i.e., firms with lower credit ratings). In contrast, the coefficient on $\Delta\hat{s}_t$ for high-investment-grade (HIG) firms is negative and statistically insignificant. In terms of economic significance, a one standard-deviation increase in the predicted change in investor sentiment leads to a 4.03% (=0.467×8.64) increase in real business investment growth for high yield (HY) firms, and a 3.24% (=0.467×6.94) increase for low-investment-grade (LIG) firms. We also test if the coefficients on $\Delta\hat{s}_t$ between HY (LIG) and HIG are statistically different, and report the

Table 6 Asymmetries

	(1)	(2)	(3)	(4)
$\Delta\hat{s}_t^+$	9.24 (1.13)	7.02 (1.37)	6.96 (1.37)	7.14 (1.40)
$\Delta\hat{s}_t^-$	5.28 (1.26)	4.10 (1.55)	4.19 (1.56)	4.22 (1.59)
$\Delta \log Y_{i,t}$		0.70*** (19.71)	0.70*** (20.54)	0.70*** (20.40)
$\Delta \log Q_{i,t-1}$		0.17*** (10.40)	0.17*** (10.45)	0.17*** (10.49)
Δcs_t			0.32 (0.51)	0.30 (0.48)
Firm FE	Yes	Yes	Yes	Yes
Industry FE	No	No	No	Yes
Observations	17,393	13,082	13,082	13,073
R^2 (within)	0.005	0.126	0.126	0.126
$P_{+=-}$	0.726	0.665	0.678	0.661

We estimate the following model: $\Delta I_{i,t} = \beta_0 + \beta_1^+ \Delta\hat{s}_t^+ + \beta_1^- \Delta\hat{s}_t^- + \beta_2 \Delta cs_t + \beta_3 \Delta \log Y_{i,t} + \beta_4 \Delta \log Q_{i,t-1} + \mu_i + \varepsilon_{i,t}$

I is real business investment which is defined as nominal capital expenditures deflated by the implicit price deflator for business fixed investment, and $\Delta I_{i,t} = \log(I_{i,t}) - \log(I_{i,t-1})$. Δcs_t is the change in the credit spread defined as the spread between yields on corporate BAA bonds and yields on 10-year Treasury securities from the Federal Reserve Economic Data (FRED), $Y_{i,t}$ is real sales defined as nominal sales from Compustat deflated by the implicit GDP deflator for the US nonfarm business sector, $Q_{i,t}$ is Tobin's Q, μ_i is the firm fixed effect. Sample period: annual data from 1985 to 2015. For all our firm-level panel regressions, we cluster standard errors by both firm and year to allow not only serial correlation within firm but also spatial correlation across firms

$^{***}p<0.01$, $^{**}p<0.05$, $^{*}p<0.1$

two-tailed p values in the last two rows of Table 5. As we can see, the *two-tailed p* values are 8% and 6%, respectively.

In Column (2), we take into account firm-level controls such as real sales growth and lagged Tobin's Q growth as in López-Salido et al. (2017). As we can see, the results are materially unchanged: while the coefficients on $\Delta\hat{s}_t$ are still positively significant for high-yield and low-investment-grade firms, the coefficient on $\Delta\hat{s}_t$ for high-investment-grade firms is again negative and statistically insignificant. Δ logY and Δ logQ enter with positive signs. This is expected, as the improvement in firm-level fundamentals should induce more investment.

In Column (3), we further include the change in the credit spread, which is a proxy for aggregate economic and credit-market conditions and is accounted for by Arif and Lee (2014). As can be seen, the results are qualitatively similar to those in column (2). Both Δ logY and Δ logQ enter with positive signs, and the coefficients on $\Delta\hat{s}_t$ are still positively significant for high-yield (HY) and low-investment-grade (LIG) firms,

In Column (4), we include the industry fixed effects to control for observed and unobserved heterogeneity across industries (e.g., industry concentration, industry investment spending). In Column (5), we use an alternative proxy of the predicted change in investor sentiment, $\Delta\hat{s}_t = \hat{a} + \hat{b}_1 s_{t-2} + \hat{b}_2 \log PE10_{t-2}$, which is based on only the benchmark sentiment predictors. In both cases, the results are materially unchanged: the predicted change in investor sentiment is only positively correlated with investment growth for firms with lower credit ratings.

Do increases and decreases in investor sentiment have asymmetric effects on firm investment? We address this issue by allowing the coefficients on sentiment increases and decreases to be different. The results are reported in Table 6. As can be seen, there does not

Table 7 Predicted change in investor sentiment and equity issuance

	(1)	(2)	(3)	(4)	(5)
$HY_{i,t-1} \times \Delta\hat{s}_t$	−0.25 (−1.13)	−0.29 (−1.36)	−0.29 (−1.39)	−0.29 (−1.31)	−0.43 (−1.22)
$LIG_{i,t-1} \times \Delta\hat{s}_t$	−0.55* (−1.91)	−0.57** (−2.06)	−0.57** (−2.06)	−0.57** (−2.08)	−0.92** (−2.19)
$HIG_{i,t-1} \times \Delta\hat{s}_t$	−0.46 (−1.52)	−0.49 (−1.61)	−0.48 (−1.57)	−0.47 (−1.59)	−0.78* (−2.03)
$\Delta \log Y_{i,t}$		−0.01 (−1.31)	−0.01 (−1.54)	−0.01 (−1.57)	−0.01 (−1.59)
$r_{i,t}$		0.01** (2.27)	0.01** (2.54)	0.01** (2.52)	0.01** (2.55)
Δcs_t			−0.06 (−0.27)	−0.06 (−0.25)	−0.06 (−0.27)
Firm FE	Yes	Yes	Yes	Yes	Yes
Industry FE	No	No	No	Yes	Yes
Observations	13,082	13,079	13,079	13,073	13,073
R^2 (within)	0.002	0.005	0.005	0.005	0.005
$P_{\mathrm{HY=HIG}}$	0.547	0.563	0.587	0.596	0.464
$P_{\mathrm{LIG=HIG}}$	0.783	0.787	0.772	0.730	0.746

The table shows the estimation results from the following model: $\Delta NEI_{i,t} = \beta_0 + \beta_1^{HY}(HY_{i,t-1} \times \Delta\hat{s}_t) + \beta_1^{LIG}(LIG_{i,t-1} \times \Delta\hat{s}_t) + \beta_1^{HIG}(HIG_{i,t-1} \times \Delta\hat{s}_t) + \beta_2\Delta cs_t + \beta_3\Delta \log Y_{i,t} + \beta_4 r_{i,t} + \mu_i + \varepsilon_{i,t}$

Net equity issuance (NEI) is defined as sale of common and preferred stock minus purchase of common and preferred stock, and $\Delta NEI_{i,t} = \frac{NEI_{i,t}-NEI_{i,t-1}}{AT_{i,t-1}}$, where $AT_{i,t-1}$ is the book value of total assets of firm i at the end of year $t-1$. cs_t is the credit spread defined as the spread between yields on corporate BAA bonds and yields on 10-year Treasury securities from the Federal Reserve Economic Data (FRED). $Y_{i,t}$ is real sales defined as nominal sales from Compustat deflated by the implicit GDP deflator for the US nonfarm business sector. $r_{i,t}$ is the total log return during firm i's fiscal year (we cumulate daily returns from CRSP over the firm's fiscal year). μ_i is the firm fixed effect. HY, LIG, and HIG are indicators of the firm's credit quality. Sample period: annual data from 1985 to 2015.HY (high yield) = BB+, BB−, BB, B+, B, B−, CCC+, CCC−, CCC, CC, C, D; LIG (low investment grade) = A, A+, A−, BBB, BBB+, BBB−; HIG (high investment grade) = AAA, AA+, AA, AA−. For all our firm-level panel regressions, we cluster standard errors by both firm and year to allow not only serial correlation within firm but also spatial correlation across firms

***$p<0.01$, **$p<0.05$, *$p<0.1$

seem to be any asymmetric effects. For instance, in Column (4), with all control variables and the industry fixed effects, the coefficients of increases and decreases of investor sentiment are 7.14 and 4.22, respectively. The p value for the difference reported in the last row is 0.66, which is not significant at any conventional levels.

Section 3 shows that the predicted change in the BW index is less likely driven by fundamental variables. Therefore, we interpret the results in Table 5 as supporting the notion that stock-market investor sentiment has casual effects on corporate investment, particularly for firms with lower credit ratings. That is, Table 5 supports Hypothesis 1. We next test if the causal effects of investor sentiment on corporate investment are due to behavioral biases of investors (Hypothesis 2) and/or corporate managers (Hypothesis 3).

4.3 Investor sentiment and equity issuance (Hypothesis 2)

The "managerial catering" hypothesis conjectures that corporate managers rationally time their stock issuances and investment to take advantage of investor behavioral biases. To test this hypothesis, we estimate Eq. (3) for net equity issuance and report the results in Table 7.

Table 8 Predicted change in investor sentiment and debt issuance

	(1)	(2)	(3)	(4)	(5)
$HY_{i,t-1} \times \Delta\hat{s}_t$	0.94** (2.19)	0.92** (2.20)	0.93** (2.09)	0.96** (2.18)	1.60** (2.39)
$LIG_{i,t-1} \times \Delta\hat{s}_t$	1.00* (1.80)	1.00* (1.89)	1.00* (1.86)	0.99* (1.79)	1.24 (1.42)
$HIG_{i,t-1} \times \Delta\hat{s}_t$	−0.23 (−0.36)	−0.19 (−0.29)	−0.21 (−0.31)	−0.21 (−0.32)	−0.45 (−0.54)
$\Delta \log Y_{i,t}$		0.04*** (4.36)	0.04*** (4.64)	0.04*** (4.52)	0.04*** (4.55)
$r_{i,t}$		−0.00 (−0.82)	−0.00 (−0.30)	−0.00 (−0.27)	−0.00 (−0.30)
Δcs_t			0.16 (0.87)	0.16 (0.86)	0.16 (0.90)
Firm FE	Yes	Yes	Yes	Yes	Yes
Industry FE	No	No	No	Yes	Yes
Observations	13,082	13,079	13,079	13,073	13,073
R^2 (within)	0.001	0.004	0.004	0.004	0.004
$P_{HY=HIG}$	0.156	0.190	0.186	0.173	0.078
$P_{LIG=HIG}$	0.047	0.060	0.059	0.069	0.036

Table shows the estimation results from the following model: $\Delta NDI_{i,t} = \beta_0 + \beta_1^{HY}(HY_{i,t-1} \times \Delta\hat{s}_t) + \beta_1^{LIG}(LIG_{i,t-1} \times \Delta\hat{s}_t) + \beta_1^{HIG}(HIG_{i,t-1} \times \Delta\hat{s}_t) + \beta_2 \Delta cs_t + \beta_3 \Delta \log Y_{i,t} + \beta_4 r_{i,t} + \mu_i + \varepsilon_{i,t}$

Net debt issuance (NDI) is defined as long-term debt issuance minus long-term debt reduction, and $\Delta NDI_{i,t} = \frac{NDI_{i,t} - NDI_{i,t-1}}{AT_{i,t-1}}$ where $AT_{i,t-1}$ is the book value of total assets of firm i at the end of year $t-1$. cs_t is the credit spread defined as the spread between yields on corporate BAA bonds and yields on 10-year Treasury securities from the Federal Reserve Economic Data (FRED). $Y_{i,t}$ is real sales defined as nominal sales from Compustat deflated by the implicit GDP deflator for the US nonfarm business sector. $r_{i,t}$ is the total log return during firm i's fiscal year (we cumulate daily returns from CRSP over the firm's fiscal year). μ_i is the firm fixed effect. HY, LIG, and HIG are indicators of the firm's credit quality. Sample period: annual data from 1985 to 2015.HY (high yield) = BB+, BB−, BB, B+, B, B−, CCC+, CCC−, CCC, CC, C, D; LIG (low investment grade) = A, A+, A−, BBB, BBB+, BBB−; HIG (high investment grade) = AAA, AA+, AA, AA−. For all our firm-level panel regressions, we cluster standard errors by both firm and year to allow not only serial correlation within firm but also spatial correlation across firms

***$p<0.01$, **$p<0.05$, *$p<0.1$

In Column 1, we only include the sentiment measures. As can be seen, there is no significantly positive correlation between the predicted change in investor sentiment and the net equity issuance growth for high-yield (HY) and low-investment-grade (LIG) firms (whose investment growth is positively correlated with investor sentiment as we show in Sect. 4.2). In Column (2), we account for firm-level controls such as sales growth and stock returns. In Column (3), we also take into account the change in the credit spread. In Column (4), we further include the industry fixed effects. In Column (5), we use an alternative proxy of the predicted change in investor sentiment, namely $\Delta\hat{s}_t = \hat{a} + \hat{b}_1 s_{t-2} + \hat{b}_2 \log PE10_{t-2}$. In all the cases, there is no significantly positive correlation between the predicted change in investor sentiment and the net equity issuance growth for firms with lower credit ratings, suggesting a rejection of the "managerial catering" hypothesis. That is, the causal effects of investor sentiment on corporate investment could not be due to that corporate managers rationally time their stock issuance and investment to take advantage of investor behavioral biases.

Table 9 Subsequent performance

	(1)	(2)	(3)	(4)	(5)	(6)
$HY_{i,t-1} \times \Delta I_{i,t}$	−0.06** (−2.16)	−0.05* (−2.03)				
$LIG_{i,t-1} \times \Delta I_{i,t}$	−0.05** (−2.09)	−0.05** (−2.09)				
$HIG_{i,t-1} \times \Delta I_{i,t}$	−0.04 (−1.03)	−0.03 (−0.85)				
$HY_{i,t-1} \times \Delta NEI_{i,t}$			0.07 (0.29)	0.06 (0.27)		
$LIG_{i,t-1} \times \Delta NEI_{i,t}$			0.20 (1.38)	0.20 (1.37)		
$HIG_{i,t-1} \times \Delta NEI_{i,t}$			0.19 (0.74)	0.18 (0.71)		
$HY_{i,t-1} \times \Delta NDI_{i,t}$					−0.17** (−2.10)	−0.17** (−2.09)
$LIG_{i,t-1} \times \Delta NDI_{i,t}$					−0.20** (−2.59)	−0.19** (−2.50)
$HIG_{i,t-1} \times \Delta NDI_{i,t}$					−0.22 (−1.70)	−0.21 (−1.70)
$\Delta \log Y_{i,t}$		−0.05 (−0.77)		−0.09 (−1.25)		−0.09 (−1.18)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	10,206	10,206	10,206	10,206	10,206	10,206
R^2 (within)	0.002	0.003	0.000	0.001	0.002	0.003

We estimate the following model: $r_{i,t+1} = \beta_0 + \beta_1^{HY}\left(HY_{i,t-1} \times \Delta X_{i,t}\right) + \beta_1^{LIG}\left(LIG_{i,t-1} \times \Delta X_{i,t}\right) + \beta_1^{HIG}\left(HIG_{i,t-1} \times \Delta X_{i,t}\right) + \beta_2 \Delta logY_{i,t} + \mu_i + \varepsilon_{i,t+1}$ where $\Delta X_{i,t}$ is $\Delta I_{i,t}$, $\Delta NEI_{i,t}$, or $\Delta NDI_{i,t}$. I is real business investment which is defined as nominal capital expenditures deflated by the implicit price deflator for business fixed investment, and $\Delta I_{i,t} = \log(I_{i,t}) - \log(I_{i,t-1})$. Net equity issuance (NEI) is defined as sale of common and preferred stock minus purchase of common and preferred stock, and $\Delta NDI_{i,t} = \frac{NDI_{i,t}-NDI_{i,t-1}}{AT_{i,t-1}}$, where $AT_{i,t-1}$ is the book value of total assets of firm i at the end of year $t-1$. Net debt issuance (NDI) is defined as long-term debt issuance minus long-term debt reduction, and $\Delta NDI_{i,t} = \frac{NDI_{i,t}-NDI_{i,t-1}}{AT_{i,t-1}}$. $Y_{i,t}$ is real sales defined as nominal sales from Compustat deflated by the implicit GDP deflator for the US nonfarm business sector. μ_i is the firm fixed effect. The dependent variable is $r_{i,t+1}$, the total log return during firm i's fiscal year $t+1$ (we cumulate daily returns from CRSP over the firm's fiscal year). HY, LIG, and HIG are indicators of the firm's credit quality. Sample period: annual data from 1985 to 2015. HY (high yield) = BB+, BB−, BB, B+, B, B−, CCC+, CCC−, CCC, CC, C, D; LIG (low investment grade) = A, A+, A−, BBB, BBB+, BBB−; HIG (high investment grade) = AAA, AA+, AA, AA−. For all our firm-level panel regressions, we cluster standard errors by both firm and year to allow not only serial correlation within firm but also spatial correlation across firms

***$p<0.01$, **$p<0.05$, *$p<0.1$

4.4 Investor sentiment and debt issuance (Hypothesis 3)

The "manager bias" hypothesis conjectures that corporate managers are also driven by investor sentiment and increase (decrease) debt issuance to overinvest (underinvest) when sentiment is high (low). To test this hypothesis, we estimate Eq. (3) for net debt issuance and report the results in Table 8.

In Column 1, we only take into account the sentiment measures. Consistent with the "manager bias" hypothesis, there is a statistically significantly positive relationship between the predicted change in investor sentiment and the net debt issuance growth for high-yield (HY) and low-investment-grade (LIG) firms. The coefficient on $\Delta\hat{s}_t$ for high-investment-grade (HIG) firms is negative and statistically insignificant. In terms of economic significance, a one-standard deviation increase in predicted change in investor sentiment leads to a 0.44% (=0.467 × 0.94) increase in net debt issuance growth for high yield firms, and a 0.47% (0.467 × 1.00) increase for low-investment-grade firms. We also test if the coefficients on $\Delta\hat{s}_t$ between HY (LIG) and HIG firms are statistically different, and report the *two-tailed p* values in the last two rows of Table 8. As we can see, the *two-tailed p* values are 16% and 5%, respectively.

In Column (2), we account for firm-level controls such as sales growth and stock returns, which has little impact on the coefficients of $\Delta\hat{s}_t$. Δ logY enters with a positive sign. This is expected, as the improvement in firm-level fundamentals may increase the credit demand.

In Column (3), we also take into account changes in the credit spread, a proxy for general economic and credit-market conditions. In Column (4), we further account for the industry fixed effects. In Column (5), we use an alternative proxy of the predicted change in investor sentiment, $\Delta\hat{s}_t = \hat{a} + \hat{b}_1 s_{t-2} + \hat{b}_2 \log PE10_{t-2}$. As we can see, in all the cases, the results are materially unchanged: the predicted change in investor sentiment is only positively correlated with the net debt issuance growth for high-yield (HY) and low-investment-grade (LIG) firms, supporting the "manager bias" hypothesis. That is, the positive correlation between investor sentiment and corporate investment for lower-rated firms should be due to that corporate managers of lower-rated firms are also influenced by investor sentiment to overinvest (underinvest) when investor sentiment is high (low).

If corporate investment and debt issuance are driven by behavioral biases, high investment/debt issuance in year t should predict poor subsequent performance, particularly for firms with lower credit ratings. We use the stock return in year $t+1$ as our firm performance measure, as the stock return is forward looking and is used extensively in related studies (e.g., Fahlenbrach et al. 2018). That is, we test our conjecture with the following model:

$$
\begin{aligned}
r_{i,t+1} = {} & \beta_0 + \beta_1^{HY}\left(HY_{i,t-1} \times \Delta X_{i,t}\right) + \beta_1^{LIG}\left(LIG_{i,t-1} \times \Delta X_{i,t}\right) + \beta_1^{HIG}\left(HIG_{i,t-1} \times \Delta X_{i,t}\right) \\
& + \beta_2 \Delta logY_{i,t} + \mu_i + \varepsilon_{i,t+1}
\end{aligned}
\tag{4}
$$

where $\Delta X_{i,t}$ is $\Delta INV_{i,t}$, $\Delta NEI_{i,t}$, or $\Delta NDI_{i,t}$. We account for $\Delta NEI_{i,t}$ for completeness. The results are reported in Table 9. In Columns (1), (3), and (5), we only include the investment or financing measures. In Columns (2), (4), and (6), we control for sales growth. In all the cases, consistent with our expectations, high investment and debt issuance in year t predict poor subsequent performance, particularly for firms with lower credit ratings. The evidence thus reinforces the notion that investor sentiment has casual effects on corporate investment through the "manager bias" channel.

5 Conclusion

In the same spirit of López-Salido et al. (2017), we use the predicted change in stock-market investor sentiment based on lagged sentiment measures, which captures an unwinding of past investor sentiment and is less likely driven by fundamental-related confounding factors, to examine the causal impact of stock-market investor sentiment on corporate investment. Furthermore, different from previous studies (e.g., Arif and Lee 2014), we examine not only corporate investment but also financing activities, because financing decisions can help test alternative explanations for the investment-sentiment relationship. We focus on two alternative explanations. The first one is the "managerial catering" hypothesis that corporate managers rationally time their equity issuance and investment to take advantage of behavioral biases of sentiment-driven stock investors. The second explanation is the "manager bias" hypothesis that corporate managers are also subject to investor sentiment and can overinvest when investor sentiment is high.

Our paper contributes to the rapidly growing behavioral finance literature. Much of the research focuses on the effects of stock-market investor sentiment on equity returns. Extending Arif and Lee (2014), we study the causal impact of stock-market investor sentiment on corporate investment. Our paper is also related to the literature on leverage and financial crises. While previous research focuses on bank loans, we provide evidence that debt issuance in the credit market is also driven by sentiment and predicts subsequent performance of firms.

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