Extrapolation and Cognitive Dissonance in the Market for Credit Risk

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Abstract. A measure of heterogeneous beliefs based on the high-frequency credit market information is associated with an increase in the firm's debt issuance and investments and a decrease in the cost of debt the following month. Inferring an elevated credit-market belief as investors' optimistic outlook on firms' prospects predicts future credit returns. Expectations move with the leverage ("moneyness") levels and correlate with risk factors. The existence of predictable mean reversion in credit market conditions reinforces these results.

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1. Introduction

How people process risky outcomes takes a central place in finance. The focus on risk has motivated a vast body of literature that explores the general equilibrium implications of uncertainty for asset prices and the deviations from Bayes' rule. The systematic deviation from the standard neoclassic models of rational decision-making also includes corporate leaders who exhibit anchoring bias, loss aversion, and overconfidence when they make pervasive corporate decisions. Much work exists to understand the general equilibrium implications of uncertainty for asset prices and on the behavior of individual consumers, small investors, or highly trained corporate leaders. However, less is known about how an unexpected increase in risk affects agents' expectation formation rules and their interaction with corporate finance behavior, which is the focus of this article.

The importance of the market prices for the corporate finance decisions stems from the fact that the agents' independent learning about some unobservable and uncertain fundamentals is a result of differences in beliefs which can directly affect the asset prices and the corporate decision making.¹ Theoretical models consider uncertainty as a precondition for differences in beliefs to matter for market prices. To improve our understanding of the link between the uncertainty and asset prices and their effects on corporate behavior— particularly in the absence of the short-selling constraints – a psychologically founded learning

¹ Scheinkman & Xiong (2003) and Buraschi & Jiltsov (2006), for example, show how the interaction and intertemporal risk sharing of agents with different beliefs affect asset prices and equilibrium risk premia. Fracassi, Petry & Tate (2016) show how credit analysts are often biased in their assessment of borrowers and that these differences are reflected in debt prices.

model that describes the dynamics of belief formation presented in this article can offer useful insights.

The information content of the asset prices in the market for credit risk provides a particularly useful foundation for this task. The rationale is grounded in theoretical and market structure factors. First, the credit risk literature has shown that the high volatility of the credit spreads can be explained by one common factor, which is not accounted for by the volatility of the fundamentals (Collin-Dufresne, Goldstein & Martin 2001, Gilchrist & Zakrajek 2012). Furthermore, this literature has documented the challenge in explaining the high degree of time clustering in defaults observed in the data even when conditioning the default intensities by all available information (Das, Duffie, Kapadia & Saita 2007). In learning from default interpretation studies, for example, the default intensities include the expected effects of the hidden covariates; where the arrival of default causes— via Bayes' rule— a jump in the conditional distribution of concealed covariates, and consequently a leap in the conditional default probabilities of all firms exposed to the same unobservable covariates.² Second, a recent phenomenon in the market for credit risk is the significant increase in “naked trading,” which permits investors to express their views on firms' future credit soundness.³ Marginal investors in this market are thus unaffected by short-selling constraints allowing for the dispersion of beliefs about firms fundamentals to affect the market-observed credit spreads.

Credit spreads are the market's assessments of the credit risk of the underlying entity, while the return of the spreads reflects the change of the risk. Return jumps are sud-

² See Jarrow & Yu (2001), Collin-Dufresne, Goldstein & Helwege (2003), Schonbucher (2003), Giesecke (2004).

³ The naked trading of CDSs consists of speculators buying protection against a default without owning the underlying credit or bond, known as synthetic positions.

den and significant movements in the risk. Yet, credit analysts routinely cluster different bonds in homogenous market cells based merely on their contribution to duration⁴—an epitome of the representative heuristic of Kahneman and Tversky— with considerable implications for the risk management when belief-driven trades cause jumps in the credit spreads. Furthermore, naked trading allows investors to take synthetic positions on firms’ debt at any time allowing for changes in beliefs at high frequency. These high-frequency variations in views on the firm’s future creditworthiness are well-matched with studies in psychology that show that probabilistic representations occur at a high rate.⁵ This context, therefore, provides for an especially useful setting to investigate the different sources of information-driven trades, such as heterogeneous beliefs, and their implications for the corporate finance decisions.

The working hypothesis of this paper is that the belief formation of investors is forward-looking – i.e., investors react to recent news – but the representativeness distorts this reaction. Investors’ beliefs contain “kernel of truth” (as in Bordalo, Gennaioli & Shleifer 2018, Bordalo, Gennaioli, Porta & Shleifer 2019), but the fallacy arises through overextrapolation; they overstate an actual feature of the data. Jumps in the asset prices have traditionally been linked to news arrivals. In the market for credit risk, they signal a sudden and substantial deterioration in the market’s assessment of the credit soundness of the underlying entity. However, for the firms in credit distress, the probability of default is often a decreasing function over time, where jumps can signal that the issuer has sur-

⁴ Duration represents the product of the percentage of portfolio market value represented by a given market cell and the average of the duration comprising that selected cell. This represents the sensitivity of the portfolio to a parallel shift in spreads across all securities constituents of the selected cell.

⁵ See Seitz, Franz & Azari (2009), for example.

vived the critical period and its financial prospects are likely to improve. Recent jumps in the credit spread, therefore, allow investors to form extrapolative beliefs. Still, they also induce investors to make judgments on their financial gains and losses arising from the recent event, as predicted by the realization utility models. It is, therefore, an empirical question to determine which belief formation rules are at work and to identify a comprehensive psychological foundation for this account.

This paper proposes a new psychologically founded model that unifies the extrapolation and realization utility models. If extrapolators' beliefs are anchored merely on past price changes, this will result in little or no trading. It is, therefore, necessary for a second channel to explain this challenge, blending extrapolation with attention to potential gains and losses. The proposed model thus combines the belief formation process, described by extrapolation, with the realization utility model, explained by the cognitive dissonance model.⁶ The goal of this paper is to study this link empirically and disentangle the different implications of heterogeneous agent beliefs for corporate decisions.

Empirically, the dispersion of beliefs is implied from a novel high-frequency credit spread returns of 96 entities over about six years.⁷ The differences in beliefs are based on credit market information alone and derived in two steps. In the first step, following Greenwood & Hanson (2013), lagged values of idiosyncratic extreme price movements of firms' credit

⁶ Cognitive dissonance in social psychology represents "cognition," a mental or thought formation process of an individual who simultaneously holds two conflicting "dissonant" cognitions.

⁷ The period spans March 2011 to December 2016, just under six years. The range of data was dictated by several criteria, including the availability of sufficiently long time series of high-frequency CDS prices, large capitalization, liquidity, and representation of a broad range of sectors.

spreads, the market-wide jumps, and illiquidity risk, as variables that have previously been shown to predict credit spread returns, are used. In the second step, following Lopez-Salido, Stein & Zakrajsek (2017), the fitted values from the first-step regression – interpreted as a proxy that captures the credit-market investors’ time-varying belief dispersion – are used in regressions to predict future credit returns, changes in firms financing mix, investment behavior, and cost of capital.⁸

The forward-looking psychological model of this paper and the empirical method employed to assess the dispersion of beliefs based on the market- “observable” firm-specific jumps, permits for more accurate modeling of the belief formation process and assures that results reported here are robust to the Lucas critique.⁹

Empirical results show that beliefs are market state variables useful in predicting credit return and correlate with firms’ issuing behavior. Dispersion of beliefs is higher for smaller and low-levered entities and conversely lower for large and high-levered firms. To the extent that leverage represents the moneyness of the implicit put option on a firm’s debt, results show that expectations move with the moneyness levels and correlate with risk factors. The positive relationship between the dispersion of beliefs and the variance risk

⁸ This two-step regression accounts for the possibility that the firm’s financing and investment behavior is not a reflection of changes in the exogenous nonfinancial factors – which would be captured by forward-looking spreads estimated in the first-step regression.

⁹ The reported risk measures are data-driven jump-to-default estimates which, traditionally in the credit risk literature, have been implied by models invoking strong parametrical assumptions. Implying the differences of beliefs from firm-level high-frequency data extends the previous studies which rely on aggregate quarterly or even yearly data to model belief rules in the credit market and thus do not allow for a clear separation between the rational decision-making and the belief formation rules.

premium is sturdier for the entities that are exposed to substantial changes in beliefs in the market. Results reported here suggest that extrapolative biases are also apparent in the high-frequency trading.

The remainder of the paper is organized as follows. Section 2. discusses the theoretical link between the differences in beliefs and the asset prices in the literature. Section 3. formally describes the psychological model of belief formation that can help to explain the main empirical findings of the article. Section 4. discusses the data set, and Section 5. presents the method used to imply the credit-market sentiment. The empirical results are reported in Section 6. and Section 7. concludes.

2. Literature review

The importance of the differences in beliefs for the asset prices holds a cardinal place in the behavioural finance literature. The dispersion of expectations in this research arises from limits to the arbitrage conjecture of Miller (1977), where market frictions affect the disagreement and, consequently, the expected returns. Harrison & Kreps (1978) show that overpricing can also occur in a dynamic setting while Scheinkman & Xiong (2003) show how, for the assets for which agents have higher levels of disagreement, overconfidence-based divergences, and a short-sale constraint can lead to overvaluation and hence lower average returns.

The overconfidence-based disagreement models, however, do not say much about the type of beliefs that agents hold. Better specification of the type of beliefs is achieved in the extrapolative beliefs model. These models assume an economy populated by extrapolators and fundamental traders and explicitly specify traders' expectations. Barberis, Shleifer & Vishny (1998) undertake early work in this regard. In this model, investors' extrapolative

beliefs stem from Kahneman & Tversky (1972, 1973) “representative heuristics,” which often leads to a fallacy known as “base rate neglect.”¹⁰ In Barberis and colleagues’ (1998) model, investors use extrapolative beliefs for the firm’s future fundamentals. Investors place too much weight on recent news of higher-than-median cash flow growth and tend to neglect the base rate; the fact that assets excessive-high growth rates cannot be sustained for a protracted period. Bordalo, Gennaioli & Shleifer (2018) and Bordalo, Gennaioli, Porta & Shleifer (2019) relate the representative heuristic and extrapolative beliefs to a crucial argument, the “kernel of truth.” This unique idea states that although people neglect the base rate in their judgments, their extrapolation nevertheless still contains a real feature of the data, and the fallacy derives from the fact that they exaggerate it. They apply this notion into a dynamic framework that they call “diagnostic expectations” to study individual stock returns and credit cycles, finding that this extrapolative mechanism is essential in both models.

The systematic deviations from the Bayesian beliefs have also been studied in the Behavioral Corporate Finance literature. Recent studies invoke prospect theory preferences for a more specific investor bias order. The consequences of reference dependence for merger pricing are studied in Baker, Pan & Wurgler (2012), while Baker, Mendel &

¹⁰ Representative heuristics is a behavioral concept that articulates how people’s perceived probability of an event is based on their perception of the extent to which the event reflects the essential characteristics of the known group or category prototype. Although this heuristic leads to good probability judgment in many cases, often it can, however, lead to error in judgment known as base-rate neglect: a cognitive error where the general, base rate information is neglected and the entire probability weight is assigned on the specific information pertinent to only a certain case.

Wurgler (2016) use dividends as a reference point. Both these studies use past prices or dividends as a reference point to infer aversion to lower prices or dividend cuts. An alternative line of inquiry in corporate behavior literature recognizes that behavioral biases can affect the corporate leader's decision-making. Manager biases in these studies include overconfidence, reference dependence, experience effects and personal "qualities" that are not present in traditional models.¹¹ Recent studies look at the role of the analysts and financial intermediary's non-standard behavior that can affect corporate decision making. Fracassi, Petry & Tate (2016), for example, show that credit analysts' biases in their assessment of borrowers do impact debt prices.

The focus of this study is on the credit market. Current research in credit behavior show how the rapid credit growth predicts deterioration in real activity (Schularick & Taylor 2012), and that expansions heavily reliant on credit are followed by deeper recessions (Jorda, Schularick & Taylor 2013). Mian, Sufi & Verner (2017) show how the growth of household debt predicts economic decline. Studies looking at the bank credit expansion in the developed countries have documented that the increases predict significant crash risk in both bank stocks and the equity markets (Baron & Xiong 2017) and that the fast loan growth in the US banking sector predicts poor loan performance and low bank returns in the future (Fahlenbrach, Prilmeier & Stulz 2017). Similarly, Greenwood & Hanson (2013)

¹¹ Malmendier & Tate (2008) link managers' overconfidence with the desire to merge. Malmendier et al. (2011); Benmelech & Frydman (2015) and Schoar & Zuo (2017) link managers' life experience with the debt aversion. Cronqvist, Makhija & Yonker (2012) link manager's personal leverage levels of home purchases to that of the corporate leverage choices while Kaplan, Klebanov & Sorensen (2012) link firm performance to the manager's behavioral characteristics.

show how the credit quality of the corporate debt declines during times of credit expansion and that the increase of junk loan share—considered as a proxy for investor sentiment—predicts low and even negative bond returns. Lopez-Salido et al. (2017) report that low credit spreads predict a rise in the future credit spreads and a decline in economic activity. Finally, Bordalo, Gennaioli & Shleifer (2018) show how the diagnostic expectations model can help in explaining how the credit market overheats.

Credit markets have also been studied in behavioral corporate finance. Almeida, Campello, Laranjeira & Weisbenner (2012) use the portion of the long-term debt held by firms just after the shock in the credit market to imply the overconfidence and corporate investments. Engelberg, Gao & Parsons (2012) focus on the role of the social connections between bankers and firms to find that social links tend to lower the firm's cost of funding, probability of future credit downgrades, and expected default risk, and increase future stock returns. Cortes, Duchin & Sosyura (2016) provide evidence of mood-induced biases in the credit decision showing how loan officers approve mortgages at higher rates on sunnier days.

This study contributes to this literature in several respects. First, reviews on the credit cycles routinely rely on aggregate macroeconomic data. Bordalo, Gennaioli & Shleifer (2018) further these studies by looking at the individual analysts' quarterly expectations of US interest rates. Their model allows for different stochastic processes of fundamentals to drive different expectation formation rules, therefore addressing the Lucas critique. However, since analysts provide forecasts of fundamentals (or firm's future earnings), studies based on forecasts need to make assumptions on a pricing model to map projections to prices and therefore returns. Returns are particularly important in the credit market as they represent the change in the risk and, hence, a change in belief formation rules. This

paper furthers these works by using market-observed prices that reflect agents' heterogeneous expectations and, therefore, results reported here are less sensitive to these types of modeling assumptions.

Furthermore, analysts' expectations in these studies are based on aggregate credit spreads and model behavior on quarterly or yearly data.¹² Modeling frameworks relying on low-frequency data limit the legitimate empirical distinction between the rational decision-making process from the belief formation rules. Studies in psychology with probabilistic perception-action-valuation models show that the probabilistic representations are formed at a high frequency and that the subsequent actions are based on the personal probabilistic representations being enhanced with probabilistic predictions of reward and cost (Seitz, Franz & Azari 2009).¹³ This study adds to these works by looking at how investors form their beliefs when faced with significant firm-specific uncertainty in the short-run and thus is robust to the Lucas critique. Second, the advent of the naked trading and, therefore, the absence of the short-selling constraints in the market for credit risk, allows for the inquiry on the role of the dispersion of beliefs in the absence of critical market frictions. Third, while the extrapolative theories provide a more accurate description of the type of beliefs that investors hold – which the overconfidence-based disagreement models lack – they still implicitly assume homogeneity of investors. This homogeneity assumption is also present in the corporate behavior literature considering biased investors. However, this assumption does not provide comprehensive insights into the trading spec-

¹² Bordalo, Gennaioli & Shleifer (2018), for example, aggregate analysts' quarterly forecast of the default risk index (the spread between the Baa Corporate Bond Yields Relative to Yields on 10-Year Treasury Constant Maturity) into yearly data.

¹³ Perception refers to the formal understanding of events; valuation allows for the attribution of personal meaning to them.

trum. If all investors bear extrapolative beliefs, this will result in little or no trading. The current study, therefore, adds to the extrapolative beliefs models the realization-utility propositions to provide a more comprehensive psychological foundation for the trading activity. Recent jumps in the credit spread allow investors to form extrapolative beliefs. Still, they also drive investors to make a judgment on the financial gains and losses arising from this recent event, and in this way, blend extrapolation with attention on potential gains and losses. This approach, therefore, aligns with psychological studies of perception-action-valuation models where personal probabilistic representations are enhanced with probabilistic predictions of reward and cost (Seitz, Franz & Azari 2009). Finally, this study investigates whether the expectations induced by extreme events influence the decisions of corporations.

The empirical focus of this paper is on jumps in the credit spreads. How people process risky outcomes holds a central place in finance, and it is a precondition for changes in beliefs to matter for asset prices. It is, therefore, important to have a fair measure of the dispersion of beliefs. This study bases its novel empirical proxy of the heterogeneity of beliefs on two notions. First, studies of the structural models of credit risk have shown that the credit spreads are too volatile relative to what could be accounted by the variability of fundamentals and that this excess volatility can be explained by a common factor (Collin-Dufresne, Goldstein & Martin 2001, Gilchrist & Zakrajek 2012). Similarly, in learning-from-default interpretations studies, the arrival of default rates includes the effects of the hidden covariates¹⁴, while Greenwood & Hanson (2013) interpret the increase in junk bond share's ability to predict negative excess returns to be more consistent with the

¹⁴ See Jarrow & Yu (2001), Collin-Dufresne, Goldstein & Helwege (2003), Schonbucher (2003) and Giesecke (2004).

hypothesis that junk share is a proxy for investor sentiment.¹⁵ Furthermore, the market-observed extreme price movements in the credit spreads coerce traders to make a judgment about future outcomes and thus increase differences in beliefs. This causes traders to deviate from the Bayes' rule, allowing for a fair measure of the dispersion of beliefs. Second, the state-contingent payoff of credit spreads is convenient to study the agents' heterogeneous beliefs, particularly in the conditions of an abrupt increase of uncertainty. In addition, they also offer a straightforward way to measure excess volatility. Next, previous studies on the extrapolative views in the credit market invoke strong assumptions on the data-generating process.¹⁶ On the contrary, results reported here are entirely data-driven and thus not subjected to model assumptions. Finally, the proposed dispersion of belief measure reported in this paper is controlled by a set of macro-sentiment measures consisting of household consumer expectation surveys (ICS), news sentiment, analysts' recommendations, and analyst disagreement, as well as a battery of standard structural models' predictors of default in all empirical tests.

This setting thus allows us to investigate several questions previously unexplored in the literature. First, the question of whether the cross-section of credit spreads is correlated with the differences in beliefs is important since the subjective valuations of the assets with left-tail-contingent events differ across agents with heterogeneous beliefs. Second, in risk-based models of differences in beliefs, agents engage in state-contingent risk-sharing with the optimists selling protection to the pessimist. The cost of protection thus increases with the level of the disagreement, which is reflected in the equilibrium prices in the

¹⁵ Consistent with this literature, we use 'sentiment' and 'differences in beliefs' interchangeably.

¹⁶ Bordalo, Gennaioli & Shleifer (2018), for example, assume an AR(1) process for the fundamentals.

cross-section of leverage levels.¹⁷ It is, therefore, an empirical imperative to determine the relation of the differences in beliefs with the pricing of the credit spreads and its variation over different business cycles. Third, is the size of the spread between the realized and implied volatility affected by the dispersion of belief? Since the range of physical and risk-neutral probability measures depend on the characteristics of the stochastic discount factor of the representative agent and agents' belief-dependent weights assigned to these two probabilities, these models imply a direct link between the differences in beliefs and the volatility spread. The delta-hedged credit portfolios allow us to investigate the exposure to belief's that stems from bearing variance risk.

3. Learning with Representativeness and Cognitive Dissonance

The proposed psychological-based learning model that describes the dynamics of belief rules in the market for credit risk is based on extrapolation and preferences. The model has four main components – the market, beliefs, learning, and preferences. Internet appendix A provides some further information on the model.

A1. A model of bubbles and the kernel of truth

Market. This part follows closely Barberis, Greenwood, Jin & Shleifer (2018) with some minor modifications. Consider an economy with $T+1$ dates, denoted by $t=0, 1, \dots, T$, in which there are two assets: a risk-free (cash) asset with returns normalized to zero and a risky asset (bond) with a fixed supply of B bonds. The risky asset is potentially subject

¹⁷ In the contingent-claim model of Merton (1974) credit risk defaults occur when assets fall below the face value of its debt; therefore, the firm's leverage represents the “money-ness” of the implicit put option on the firm's debt.

to bubbles and derives a claim to the protection seller of S_T spreads paid quarterly and on the final date T of the insurance contract. The protection seller collects payment of S_t during the life of the contract given by

$$\tilde{S}_T = S_0 + \tilde{s}_1 + \cdots + \tilde{s}_T \quad (1)$$

where $\tilde{s}_t \sim N(0, \sigma_s^2)$, i.i.d. over time. S_0 is public information on date 0, while s_t becomes public at time t . The price of the risky asset P_t is determined endogenously.¹⁸

Beliefs. As in Barberis, Greenwood, Jin & Shleifer (2018), there are two types of traders in the economy, fundamentals, and extrapolators. Fundamental traders are boundedly rational – i.e., at each stage, they learn from the past to determine their time t demand, and they maximize a constant absolute risk aversion (CARA) utility function defined over the next period's wealth. In this backward induction process of determining the demand, however, this type of traders assumes that other agents in the economy will keep their per capita share of supply of the risky asset constant. These investors, therefore, do not have a full understanding of how other agents in the economy form their demand. Consequently, their share is determined by their expected price change of the risky asset in the next period scaled by their risk aversion and by their estimate of the risk.

Extrapolators are the second type of traders. These investors also maximize CARA utility. Further, their belief about the next periods expected price change of the risky asset is a weighted average of past price changes, where the more recent price changes are weighted more heavily. Extrapolators, however, pay some attention to how the price of

¹⁸ See Longstaff & Wang (2012) about the endogenous determination of the credit sector's size.

the risky asset relates to its fundamental value. The extrapolator's i demand is therefore

$$w_{i,t} \left(\frac{S_t - \gamma \sigma_\varepsilon^2 (T - t - 1) B - P_t}{\gamma \sigma_\varepsilon^2} \right) + (1 - w_{i,t}) \left(\frac{X_t}{\gamma \sigma_t^2} \right), \quad (2)$$

the weighted average of fundamental traders demand, captured by the first component of Equation (2), and its own demand, captured the second part of Equation (2). The weight w_i of extrapolators' demand is time-varying in t and independent among extrapolator types. γ and σ_t^2 represent traders' coefficient of absolute risk aversion and idiosyncratic risk, respectively. Finally, $X_t \equiv (1 + \theta) \sum_{k=1}^{t-1} \theta^{k-1} (P_{t-k} - P_{t-k-1}) + \theta^{t-1} X_1$ where $\theta \geq 0$ and X_1 is a constant that measures extrapolator enthusiasm at time 1.

Learning. Traders' learning process reflects that reported in Bordalo, Gennaioli, Porta & Shleifer (2019). Traders learn about the firm's unobserved fundamentals f from a noisy signal, and they adjust their expectations in the direction of the current surprise; i.e., the extreme price movements in the firm's credit spreads. This process leads to a distorted Kalman filter: overinflating the probability of future outcomes whose probability has factually increased in the light of the recent news.

At time t the market observable noisy signal of firm i is

$$\bar{x}_{i,t} = b x_{i,t-1} + f_{i,t} + \epsilon_{i,t}. \quad (3)$$

The mean-reversion of the signal is defined by $b \in [0, 1]$ while the firm's fundamentals are captured by f which grows as

$$f_{i,t} = a \cdot f_{i,t-1} + \eta_{i,t} \quad (4)$$

where $a \in [0, 1]$ captures its persistence. $\epsilon_{i,t}$ and $\eta_{i,t}$ in equations (3) and (4) are the transitory i.i.d. normally distributed shocks of the signal $(0, \sigma_\epsilon^2)$ and fundamentals $(0, \sigma_\eta^2)$ while the stationarity is assumed by imposing $b \leq a$.

As the traders do not observe the f , the Kalman filter describes the distribution of the forecasted f at any time t conditional on the firm's past and current market observable signal $(x_{i,u})_{u \leq t}$ with mean

$$\hat{f}_{i,t} = a\hat{f}_{i,t-1} + K(x_{i,t} - bx_{i,t-1} - a\hat{f}_{i,t-1}) \quad (5)$$

and variance σ_f . The current forecast of firms' fundamentals, therefore, includes the past information on f and it is adjusted in the direction of the current surprise $x_{i,t} - bx_{i,t-1} - a\hat{f}_{i,t-1}$. The extent of adjustment increases in K with $K \equiv \frac{a^2\sigma_f^2 + \sigma_\eta^2}{a^2\sigma_f^2 + \sigma_\eta^2 + \sigma_\epsilon^2}$. K , therefore, represents the signal-to-noise ratio and separates the transitory from the persistent signal shocks ($\eta_{i,t}$ from $\epsilon_{i,t}$). The adjustment is complete ($\hat{f}_{i,t} = x_{i,t} - bx_{i,t-1}$) when transitory shocks are non-existent ($\sigma_\epsilon^2 = 0$) while the signal becomes noisier with the increase in the frequency of transitory shocks.

However, once the traders observe the current surprise signal (the jump in the credit spreads) $x_{i,t} - bx_{i,t-1} - a\hat{f}_{i,t-1}$ they infer firms' fundamentals f — whose true conditional distribution is normal with variance σ_f^2 and mean as in Equation (4)— by overweighting the surprise signal due to the representative heuristics and neglecting the base rate (Tversky & Kahneman 1974). The abrupt changes in the market's assessment of the credit risk, therefore, lead to a distorted Kalman filter.

A2. Cognitive dissonance

Preferences. Although the extrapolative theories provide a more accurate description of the type of beliefs that investors hold, they still implicitly assume homogeneity of investors. If all investors bear extrapolative expectations anchored merely on past price changes, this will result in little or no trading. The current study, therefore, adds to the extrapolative beliefs models the realization-utility propositions to provide a more

comprehensive psychological foundation for the trading activity, and therefore providing a unified psychological model on investor's behavior.

The model is the one proposed by Chang, Solomon & Westerfield (2016), the modified version of the realization utility model of Barberis & Xiong (2009, 2012). In addition to receiving disutility from realized losses, Chang and colleagues' model also assumes that investors experience a psychological cost from the paper losses – i.e. even when the assets are not sold. Furthermore, the size of the utility surprise that investors receive when realizing gains and losses is a function not only of the magnitude of the gain and losses, but, more importantly, on the degree to which the individual feels responsible for the original investment decision. The paper losses capture the notion of dealing with cognitive dissonance by misrepresenting or ignoring the negative news. In contrast, the responsibility for the initial investment decision captures the idea of dealing with the cognitive dissonance by adding ameliorating cognition. These are the two main channels for resolving cognitive dissonance.

As previously, there is a riskless and risky asset and the model assumes a three-period ($t \in \{0, 1, 2\}$) discrete-time framework. Each risk-neutral investor i starts at time $t = 0$ with wealth W_0 , and in the final period, the investor consumes W_2 . The price of the risky asset is normalized using the risk-free asset

$$\frac{P_1}{P_0} = 1 + \mu_{i,t-1} + e_{t-1}, \quad (6)$$

where $\mu_{i,t-1}$ is investor i 's posterior expected return (described later), and e_{t-1} is mean-zero noise. At time $t = 0, 1$, the investor can choose to allocate their wealth between the risk-free asset and the risky asset. The investor's wealth, therefore, evolves according to

$$W_{i,t} = W_{i,t-1} + W_{i,t-1}x_{i,t-1} \left(\frac{P_1}{P_0} - 1 \right), \quad (7)$$

where $x_{i,t-1}$ is the fraction of the investor's wealth invested in the risky asset.

At time $t = 1$, before the trading, investors with a heterogeneous valuation on firms fundamentals experience surprise to their valuation. This shock changes the posterior expected return for each investor with

$$\mu_{i,1} \sim \text{cdf } G\left(\mu; \frac{P_1}{P_0}\right). \quad (8)$$

G is the cumulative density function that describes the posterior distribution. When past returns rise we have $\frac{\partial}{\partial P_1}G < 0$ and when past returns fall we have $\frac{\partial}{\partial P_1}G > 0$. The expected magnitude of the disposition effect is therefore

$$EDE \equiv E[G(0; P_1) | L_1 = 0] - E\left[G\left(\phi(1 - \delta - \xi)\frac{L_1}{W_1}; P_1\right) | L_1 < 0\right], \quad (9)$$

where $L_{i,t} \equiv \min\{0, P_t - P_{t-1}\} \leq 0$ represents the loss that investor faces when the price of the risky asset declines. If G is decreasing in P_1 then $(P_1 | L_1 = 0) > (P_1 | L_1 < 0)$ implies that the expected disposition effect is negative for nearly rational agents. In contrast, if G is increasing in P_1 the expected disposition effect is positive for nearly rational agents. From Equation (9) the expected disposition effect is positive when ϕ is large, and δ is small, and vice versa.

$\phi > 0$ is a measure of ego cost, and $\xi \in [0, 1]$ measures the extent to which an investor must pay the ego cost of being wrong if he does not realize his losses. The psychological cost is a disutility from being wrong, $\xi\phi L_{i,t}$. For the assets in which the traders have taken an investment decision originally (i.e., non-delegated assets such as individual stock), investors' reluctance to realize losses relative to gains could lead them to downplay the negative information and adopt inaction, thereby creating a positive disposition effect. Alternatively, for the delegated assets (i.e., mutual funds), the investor could choose to bring an ameliorating cognition by blaming someone else for the losses, and thus they can

sell the asset without experiencing the realization utility associated with admitting they were wrong. In this case, the realization utility from selling an asset at a loss can be reduced from $\phi L_{i,t}$ to $(1 - \delta)\phi L_{i,t}$ where $\delta \in [0, 1]$ represents the extent to which loss-disutility can be lessened by blaming others. This shift of responsibility alleviates traders' pain associated with losses under cognitive dissonance and thereby creates a reverse-disposition effect.

A3. Trading and Model Predictions

At the core of the trading in the market for credit risk is the possibility for the investors to express their beliefs on future changes in the credit spreads. If an investor believes that the underlying entity's credit quality is deteriorating, she can buy a CDS protection (going short) and, speculatively, if she believes that the company's soundness has improved, the investor can sell protection (going long). An essential aspect of this market is that investors can have synthetic positions on the firm's credit – i.e. investors can go long (short) on credit protection without any upfront cost of buying (selling) the underlying credit.¹⁹ The synthetic positions thus resemble the delegated positions in an asset. This allows for different sources of information-driven trades, such as heterogeneous beliefs, to take place. The market observed jumps in the credit spreads, therefore, signal sudden and large deteriorating changes in the market's assessment of the credit risk of the underlying entity, but they can also imply the issuer has survived the critical period and its financial health is likely to have improved since often the probability of default of the distressed entities is a decreasing function of time. It is this Λ -shaped trade where the sudden and

¹⁹ The synthetic positions also do not bear limits on the trading volume leading to concerns about systematic risk. Empirically this source of risk is captured with the market-wide jumps; namely co-jumps. The estimation procedure is discussed in Appendix B.

substantial increases in the firm's credit spreads above its fundamentals induce investors with non-delegated credit positions to buy protection (what Barberis, Greenwood, Jin & Shleifer (2018) call the "fear" effect), and investors with delegated credit positions to exhibit reverse-disposition effects and sell protection (in Barberis and colleagues' words the "greed" effect) that describes the dynamics of the belief formation process in the market for credit risk.

PROPOSITION 1: If investors are rational ($\theta=0$), they make no systematic error in predicting the growth of the firm's future fundamentals. However, expectations can generate extrapolation of fundamentals leading investors to systematically overestimate the firm's forecasted growth and therefore increase the firm's financing.

PROPOSITION 2: For riskier firms, due to their higher beta (sensitivity to aggregate conditions), lower optimism and thus higher credit spread at time t causes a large rise in the credit spreads and disproportionate decline in debt issuance and investments.

PROPOSITION 3: If investors have great cognitive dissonance, they will display a more substantial disposition effect in non-delegated credit positions (for those that they effectively hold the underlying credit) and reverse-disposition impact in delegated credit positions; i.e. in synthetic positions in the credit.

4. Data set

The data set comes from Bloomberg and spans March 9, 2011 to December 10, 2016. The credit default swap prices come from Credit Market Analysis Ltd (CMA) DataVision via the Bloomberg data service. The data set consists of 5-minute intra-day values for the 5-year CDS spreads for 96 entities constituents of the CDX NA IG index. CMA is the most widely used database among financial market participants, and it is the principal

data source for Bloomberg-disseminated CDS prices; thus, these data also contain fewer errors.²⁰ Trading days with less than 40 observations of 5-minute returns and the repeated observations are also deleted.²¹

Previous literature bases the sentiment proxy on the firm- and equity market-based information as found by Baker & Wurgler (2006) or household consumer expectation surveys, published as an Index of Consumer Sentiment (ICS) by the University of Michigan. To investigate whether the explanatory power of the proposed expectations measure for the future firms' issuing behavior is superior to the traditional macro sentiment measures, this study uses the ICS measure as a macro sentiment control variable throughout its empirical tests.

The strong links between idiosyncratic volatility and news have been frequently emphasized in the volatility literature. However, it is challenging to observe the news, mainly because some announced news may be anticipated. Hence, in this literature, the news is customarily defined as a residual price movement within the context of a predictive model. Furthermore, having observed that firm-level volatility exhibits periods of high volatility, several studies advocate that news arrival patterns should be classified in accordance with the volatility dynamics into (a) the normal news flow and (b) unusual news events (or the

²⁰ CMA quotes provided by Bloomberg have been extensively used in the literature; for example, Das, Hanouna & Sarin (2009), Saretto & Tookes (2013), Das, Kalimipalli & Nayak (2014) and Boehmer, Chava & Tookes (2015).

²¹ Internet appendix B provides additional information on the data used in this article. The selection of data was dictated by several criteria, including the availability of a sufficiently long time series of high-frequency CDS data, large capitalization, liquidity, and representation of a broad range of sectors.

unusual news flow) that are characterized by volatility shocks and subsequent periods of high volatility (e.g., Andersen 1996, Maheu & McCurdy 2004).

Accordingly, this study controls for news sentiment effects. The daily news sentiment data (NEWS SENTIMENT) reported by Bloomberg uses machine-learning techniques to identify news stories or tweets relevant to an individual stock. Bloomberg then assigns a sentiment score, -1 being the most negative to 1 for positive and 0 neutral, to each article or tweet in the feed. An additional control variable constitutes Bloomberg's estimate of ANALYST RECOMMENDATIONS rating scales. The rating scales range between '1' and '5' where a return of '5' is the most influential ranking (buy or similar), while a return of '1' is the weakest (sell or similar). Further, following Bali, Bodnaruk, Scherbina & Tang (2017) the analyses include measures of analyst disagreement estimated as the standard deviation of earnings' forecasts divided by the absolute value of the mean earnings forecasts (as reported by Bloomberg) which constitutes another firm-specific control variable (ANALYST DISAGREEMENT). Bloomberg's daily data are averaged into a monthly frequency in the empirical analysis.

Since credit spreads are sensitive to macroeconomic changes, this study controls for equity option implied volatility index (VIX) to control for investors' consensus view of future (30-day) expected stock market volatility. Other macroeconomic control variables include 3-month Treasury yields (SHORT RATE) and, Fama-French bond factors: (TERM SPREAD) – the difference between the yields on 10-year- and 3-month Treasury securities; and the default risk factor (DEF) – the difference between the return on a market portfolio of long-term corporate bonds and the long-term government bond return. Additional macroeconomic variables employed are the returns on the S&P 500 index, real GDP per capita (GDP), and CPI inflation rate.

Finally, balance-sheet control variables employed in this study include the return on equity (ROE), the dividend payout ratio estimated as dividend payout share divided by equity price (DIVIDEND), and the leverage ratio – the sum of current- and long-term debt divided by the sum of total equity and current- and long-term debt – (LEVERAGE). Further, the empirical corporate finance literature demonstrates that the leverage increases with firm's size (SIZE). This is because larger firms are better diversified and have lower default probabilities and lower associated bankruptcy costs, which in turn allows them to take on more leverage. The firm size is, therefore, commonly assumed as an inverse proxy for the expected cost of bankruptcy (Rajan & Zingales 1995, Beck, Demircuc-Kunt, Laeven & Levine 2008). Consequently, this study controls for firm size effects which is proxied as a log of total sales.²² Final balance-sheet control variables include after-tax weighted average cost of debt and equity, and firms' short-term debt, as reported by Bloomberg.

5. Empirical method

5.1 Time-varying jump risk

To measure volatility and jump risks, the market observable credit spreads need to be translated into returns. A corporate bond can be regarded as a combination of a risk-free bond and a risky asset that pays out an annual coupon and demands payment if a credit event occurs. This risky asset accurately reflects the CDS contract; its payoff can be

²² For robustness, this study also employs the market capitalization (results available on request), as an alternative measure of a firm's size, as suggested in the literature (Dang, Li & Yang 2018). They find that the studies on the capital structure are the most robust in terms of the choice of the size proxy.

synthesized by going long on a corporate bond and shorting the riskless bond. Consider an investor who sells protection using a CDS contract j at time $i-1$, where i is the i^{th} intraday observation within trading day t at a CDS spread of $CDS_{j,t,(i-1)}$, paid quarterly. At time i within trading day t , the investor buys an offsetting contract at a spread $CDS_{j,t,i}$. The net cash flow generated prior to maturity or default is therefore $\frac{1}{4}(CDS_{j,t,i} - CDS_{j,t,(i-1)})$.²³ Since, as from the discussion in the previous section, spreads follow relative rather than absolute changes, the i^{th} within-day excess returns of contract j are modeled as

$$R_{j,t,i} = \frac{CDS_{j,t,i}}{250} - D_{CDS_{j,t,i}}(CDS_{j,t,i} - CDS_{j,t,(i-1)}), \quad (10)$$

where $D_{CDS_{j,t,i}}$ is the risky duration. These are returns to a CDS seller similar to Kelly, Manzo & Palhares (2017) and represent insurance sellers' accrued risk premia.²⁴

Recent advances in volatility estimations based on intra-day data as proposed by Andersen, Bollerslev, Diebold & Ebens (2001) and Barndorff-Nielsen & Shephard (2001) allow for a more precise estimation of the realized volatility:

$$RV_{j,t,i} \equiv \sum_{i=1}^m (R_{j,t,i}^2) \rightarrow \int_{t-1}^t \sigma_s^2 ds + \sum_{i=1}^m (J_{j,t,i}^s)^2, \quad (11)$$

²³ This specification of absolute changes in spreads follows Bongaerts et al. (2011). Longstaff et al. (2011) discount each cash flow by the risk-free rate plus the CDS spread only.

²⁴ When returns are estimated as the absolute change in spreads as in Bongaerts, De Jong & Driessen (2011), results generally remain consistent. Estimating returns from Equation (10) is a more conservative approach due to the asymmetric nature of the spreads. In those firms with low spread levels, it is difficult to generate high volatility without making CDS returns highly predictable, which is the case when returns are estimated as absolute changes in spreads. Therefore, there is more scope for CDS spreads to vary when they are high.

where $R_{j,t,i}^2$ is the squared spread return estimated in Equation (10). By using bipower variation measures the realized volatility can be separated into continuous (RVC) and jump (RJV) components.²⁵ To identify the jumps, this study uses Tauchen & Zhou (2010) extension of the “significant jump” approach of Andersen, Bollerslev & Diebold (2007), based on the signed square root of the significant jump:

$$J_{j,t,i}^s = \text{sign}(R_{j,t,i}^s) \times \sqrt{RV_{j,t,i} - BV_{j,t,i}} \times I(z > \Phi_\alpha^{-1}), \quad (12)$$

where Φ is the cumulative standard normal distribution function, α is the significance level of 0.99 of the z -test, and $I(z > \Phi_\alpha^{-1})$ is the indicator function pertaining to whether there is a jump during day t . The approach proposed herein relies on the economic intuition that jumps in financial markets are rare and large. This method, therefore, allows for credit market-based sentiment measure to be based on “observed” realized jumps without any stringent assumptions on the jump distribution.

However, since jumps can be generated by either firm-specific or common-market news, in a well-diversified portfolio, the idiosyncratic part of the jumps can be diversified away, leaving only the market-wide induced jumps – namely, the cojumps. By considering the cross-covariances within a large panel of returns, Bollerslev, Law & Tauchen (2008) propose a test for *cojumps* (CoRJV) used in this paper as an additional control variable in implying the credit sentiment measure. Internet appendix C briefly summarizes this method.

²⁵ BV allows for decomposing the summation of the squared increments (of the quadratic variation) into separate summations of small and large price changes $BV_{j,t,i} \equiv \frac{\pi}{2} \sum_{i=2}^m |R_{j,t,i}| \cdot |R_{j,t,i-1}| \rightarrow \int_{t-1}^t \sigma_s^2 ds$. [See Barndorff-Nielsen & Shephard (2004) and Huang & Tauchen (2005), among others.]

5.2 Liquidity risk

Given the intertwined nature of (extreme) price movements and liquidity risks and the opaque and fragmented nature of the market for credit risk, a measure for liquidity risk should account for these market microstructure noises. Therefore, in the empirical analysis, four different measures of liquidity risk are employed. The first one is the γ measure of illiquidity proposed by Bao, Pan & Wang (2011). This method relies on the leading feature of the illiquidity. Since the transitory price movements lead to negatively serially correlated price changes, the negative of the autocovariance in relative price changes gives a meaningful measure of illiquidity.²⁶ The second liquidity measure used in the study is Barclay's Liquidity Cost Scores (LCS), which represents the cost of a round-trip institutional-size transaction. LCS represents the round-trip cost of immediately executing a standard institutional trade.²⁷

Since it is likely that the investors consider not only the current level of liquidity in the market for credit risk but also the possible future levels in case investors need to exit the position, we also control for the variability of both γ and LCS and their corresponding risk measures (standard deviation of daily estimates over a week and aggregated into a monthly frequency, γ_risk and LCS_risk , respectively). Thus, the first principal component

²⁶ This is effectively the Roll (1984) measure of liquidity which works best with higher frequency data.

²⁷ The gamma measure is defined as the negative autocovariance in the relative log price changes $\gamma = -Cov(\Delta p_t, \Delta p_{t+1})$. LCS is defined as: $LCS = \frac{Ask\ price - Bid\ price}{Bid\ price}$. A higher LCS value is indicative of lower liquidity.

(PC) of monthly estimates of γ , LCS and their risk measures constitute the measure of the liquidity risk λ .²⁸

Table 1 provides summary statistics of the credit risk measures used in implying the credit-market sentiment. The 96 sampled firms are divided into four S&P (Moody's) credit-rating categories; AA- credit-rating category has 4 entities, followed by A- credit-rated category with 28 entities, BBB- with 51 entities and BB- credit-rated category with 13 entities as reported by Bloomberg. The sampled firms come from a diverse industry sector with the largest sector representing the consumer cyclical with 21 entities, followed by consumer non-cyclical with 19 entities and industry and financials, each having 16 entities. The communications industry has 8 entities, while technology and energy sectors have 4 entities each, and the utilities only have 2 entities. The realized jump volatility measure is time-varying with a low first-order autoregressive AR(1) coefficient of 0.23. Market-wide jumps display somewhat higher persistence with an AR(1) of 0.57.

5.3 Credit-market sentiment

The extreme price movements are commonly associated with unusual news events. Volatility shocks tend to coincide with higher levels of disagreement. Healy & Palepu (2001) argue that public news announcements reduce the level of informational asymmetry and, hence, discord in the market. However, Harris & Raviv (1993) show that when agents use differ-

²⁸ The first component explains about 64% of the variation in the liquidity variables. These results thus can be viewed as an equally weighted linear combination of the γ , LCS and their associated risk measures which allows defining λ as an evenly loaded factor on these liquidity proxies that does not load on other liquidity measures, similar to Dick-Nielsen, Feldhutter & Lando (2012) approach.

ent valuation models and interpret new information differently, information arrivals will lead to increased disagreement levels. The unusual firm-level news flow is thus likely to increase rather than to decrease levels of investor disagreement. The credit-market proxy of investors' sentiment adopted in this paper is based on the premise that the observed firm-level extreme price movements induce disagreement on future default probabilities of the firm. However, firm-specific extreme price movements are also dependent on market-wide news arrivals and the illiquidity shocks. These factors are also relevant for the models with extrapolative beliefs (as in Bordalo, Gennaioli & Shleifer 2018, Bordalo, Gennaioli, Porta & Shleifer 2019) where the overreaction also derives from public information; thus, the beliefs proxy also accounts for these factors. Once the idiosyncratic jump risk, cojumps and illiquidity measures have been estimated the credit-market dispersion of beliefs proxy is implied from the following two-step regression specification:

$$\Delta s_{t,j} = \alpha + \beta_1 RJV_{j,t-1} + \beta_2 CoRJV_{t-1} + \beta_3 \lambda_{j,t-1} + \epsilon_{t,j} \quad (13)$$

$$\Delta y_{t+1,j} = \alpha + \gamma_1 \Delta \hat{s}_{t,j} + \phi' \Delta x_{t-1} + \text{Firm } FE + \text{Month } FE + \nu_{t,j} \quad (14)$$

where $RJV_{j,t-1}$ is the one-month lagged values of firm-specific jump risk estimated in Equation (12) and the monthly lagged values of $CoRJV_{t-1}$ are implied from the method proposed by Bollerslev, Law & Tauchen (2008) and account for market-wide jumps; namely the cojumps. Finally, $\lambda_{j,t-1}$ is the one-month lagged illiquidity measure. The fitted values of Equation (13), $\Delta \hat{s}_{t,j}$, are interpreted as a proxy that captures the credit-market investors' time-varying dispersion of beliefs.

The realized volatility is not included in the model specification since cumulated Brownian motion shocks can derive from the normal functioning of the markets, while we are interested only in the extreme price movements that can induce disagreement among

investors. These ‘observed’ jump-to-default price movements prompt investors to form extrapolative beliefs on firms’ future prospects and make judgments on their financial gains and losses, as predicted by the realization utility models.

The effects of the changes in the credit-market sentiment ($\Delta\hat{s}_{t,j}$)— together with (or without) the traditional macro sentiment, credit, macroeconomic and balance-sheet factors ($\phi'\Delta x_{t-1}$)— on firms’ financing mix and investment behavior ($\Delta y_{t+1,j}$) are thus estimated as in Equation (14), while at a firm-level analysis they also control for a firm (Firm *FE*) and time (Month *FE*) fixed effects. The same specification is then used later in the paper to test the effects of the changes in the beliefs in the credit market on investments, and cost of debt and equity in Section 6.4.

6. Empirical results

Asset pricing models with Epstein-Zin utility preferences imply the desire of investors to hedge news about future uncertainty. Similarly, models with agents with different beliefs engaged in intertemporal risk-sharing – established in Scheinkman & Xiong (2003) and Buraschi & Jiltsov (2006) among others— show that these transactions can impact the stochastic discount factor (SDF) and thus affect not only the expected returns but also the volatility risk premium. If the proposed beliefs measure is a market state variable, it should contain useful information in predicting returns.

The initial analyses of the relation between the credit-market sentiment and its predictive ability on future credit returns involve sorting credit spreads into low- to- high-belief quartiles. Further, next month’s equal-weighted portfolio credit returns are estimated, as well as the corresponding five-factor alphas which are reported in Table 2.

Credit spreads sorted in the low quartile changes in beliefs have earned an average equal-weighted return of about -40 bps in the following month. The highest sentiment quartile-sorted portfolios have earned a much higher next month's return – 118 bps on average. In non-tabulated results, the monthly return differential between the high- and low-credit-sentiment sorted portfolios is about 160 bps (t-statistic 2.68) for the equal-weighted portfolios.

Columns four and five in Table 2 report the average portfolio values for firms' leverage and size measures. Values of leverage and size go hand in hand; the leverage increases with the size. This supports the notion that due to the superior diversification, larger firms have lower default probabilities and expected bankruptcy costs, which enables them to take on more leverage. The size is, therefore, an inverse proxy for the expected cost of bankruptcy.²⁹ More to the point, an interesting finding reported in Table 2 is that the leverage and the size are inversely related to the proposed credit-market beliefs measure. Larger firms are associated with lower divergence in belief values, and conversely, smaller firms have high belief values. These results suggest that the differences in beliefs in the credit market capture relevant information for the expected states of financial distress of the companies.

The following two columns (six and seven) of low-to-high quartile portfolios sorted on credit-market sentiment in Table 2 display concave patterns in the net debt issuance and convex patterns for the net equity issuance with a correlation of -0.6 – a pattern suggesting a segmented-market model.³⁰ These initial findings highlight the possible relationship

²⁹ See discussions in Rajan & Zingales (1995).

³⁰ The negative correlation between the debt and equity issuance has also been found by Lopez-Salido, Stein & Zakrajsek (2017) and Ma (2018). See also Titman (2002), who suggests that corporate bond and stock markets are not integrated.

between the differences in beliefs in the credit market and the firms' issuing behavior warranting further consideration, which is addressed later in the paper.

Another interesting result showing the informational utility of the credit-market sentiment measure, concerning the changes in the market's assessment of riskiness of the underlying entity, comes from the estimated alphas, which represent protection sellers' excess returns. The negative alphas for the lowest-sentiment quartile-sorted portfolios provide further evidence of the market's enhanced judgment on the credit risk of the underlying entity. It is the high-sentiment quartile entities that, while having on average lower leverage levels but who are of smaller size, are subjected to higher levels of differences in beliefs. This is further supported by the monotonically increasing spread levels – from the lowest-beliefs quartile to the highest (second column in Table 2). These results are substantiated in the cross-sectional predictive regressions reported in Table I.A.1 in the internet appendix, providing initial confirmations that the variations in beliefs are a market state variable.³¹

³¹ Results of the cross-sectional regressions suggest that the sentiment is statistically significant and an economically important predictor. A one-standard-deviation shock in daily sentiment (6.135) predicts an increase in spread returns by about 120 bps. The coefficients of the sentiment are stable even after controlling for other investors' sentiment and attention proxies as well as the macro-financial and balance-sheet measures, as suggested by the credit risk literature. However, once the stock returns are controlled for, as the primary driving force in explaining capital structure (Welch 2004), the coefficients of the sentiment decrease significantly, although they remain statistically significant.

6.1 Beliefs and risk premia

The previous analysis reveals the critical link between the differences in belief and the returns, leverage, and firms' issuing behavior. The importance of the credit returns stems not only from the fact that they represent markets' changed risk assessment of the underlying entity but also because the pricing kernel depends on both cash flows and the differences in beliefs. Dumas, Kurshev & Uppal (2009), for example, show how overreactions of the overconfident investors to a public signal causes excess volatility under the physical measure, and therefore characterizes the link between the volatility of the expected growth and the stochastic process for the differences in beliefs. In models with differences in beliefs, in equilibrium, agents engage in state-contingent risk sharing with pessimists purchasing protection from the optimists. Since marginal rates of substitution across states depend on agents' expectations, the higher the difference in views imposes higher equilibrium cost of protection required by the optimists to provide insurance. This has direct implications for equilibrium credit prices in the cross-section of moneyiness levels since bondholders are insurance writers on the firm's assets. Therefore the differences in beliefs can be marked across different moneyiness levels.

In Merton's model, default occurs when the firm's asset value falls below the face value of its debt. Therefore, the firm's leverage ratio defines the "moneyiness" of the put option implicit in its debt. We pay particular attention to this factor in our analysis. Plots of beliefs-sorted equally-weighted credit return portfolios in Figure 8. reveal the highest Sharpe ratios (continuous line) for the deep-out-of-the money entities— i.e. entities with

lowest leverage levels.³² Leverage has an increased value in times of low expected growth and increased uncertainty. High-levered firms have a ratio of debt to assets close to one, leaving little buffer between asset value and the default boundary. On the other hand, low-leveraged firms would need to suffer catastrophic deterioration of their assets before reaching default. It is, therefore, an interesting result that the market particularly prices the low-levered- high- differences in beliefs entities.

This result offers support to the notion that the differences in beliefs capture markets' crash-risk fears. Barberis, Greenwood, Jin & Shleifer (2018), for example, show that during a bubble extrapolators dither between the views that the recent positive news might persist, and thus should take a long position in the market, and the opposing notion that the prices are too high relative to fundamentals and thus trigger concerns over a likely future crash risk and consequently take a short position.³³ Investors' extrapolation allows for negative expected excess returns, predicting a deteriorating in issuer quality in periods of low defaults or high credit returns. This is consistent with our findings and suggests that by learning from the recent events in the market for credit risk, investors may play a role in influencing expectations.

³² Recall from the results in Table 2 that leverage (and firms' size) is inversely related to beliefs; i.e. low-beliefs quartile portfolios have the highest leverage levels, and conversely, firms with the highest dispersion in beliefs are those with lowest leverage levels.

³³ Gennaioli, Shleifer & Vishny (2012) show that the crash risk is highest following a long quiet period since the availability heuristic leads people to underestimate the chance of a crash and hence to take significant, levered positions in risky assets. In the long run, this leaves financial markets vulnerable to future negative fundamental news and makes a crash more rather than less probable.

Next, the implicit put option gives credit returns a mechanical loading on shocks to the underlying asset. In the neoclassic literature beliefs enter the SDF which allows us to examine the belief's exposure that stems from bearing variance risk. Firms are sorted in portfolios based on their dispersion of views. The delta-hedged portfolios are constructed by taking a short position in CDS and an offsetting position in the firm's equity. Formally,

$$R_{H_{p,t}} = R_{CDS_{p,t}} - \Delta_{p,t} \times R_{EQUITY_{p,t}}. \quad (15)$$

The hedge ratio is estimated from a full sample regression of CDS returns for portfolio p onto the underlying equity return.

Plots of the beliefs-sorted equally-weighted credit return portfolios reported in Figure 8. reveal the highest delta-hedged Sharpe ratios (dashed line) for the entities with significant changes in beliefs. The unhedged Sharpe ratios (continuous line) are qualitatively similar to the delta-hedged Sharpe ratios; they increase with the rising in the dispersion of expectations.

These results suggest that beliefs directly affect the pricing kernel and are thus correlated with the variance risk premium. The positive relationship between the dispersion of expectations and the variance risk premium is sturdier for the entities that are subjected to significant changes in beliefs in the market. Differences in opinions, therefore, can potentially help to resolve the low leverage puzzle as it supports the notion that firms do not increase leverage as doing so incurs a market risk premium.

6.2 Beliefs and financing mix

A firm's issuing behavior attracts considerable attention in the literature. Empirical studies are routinely based on firm-, industry-, or market-level characteristics to explain corporate issuing behavior, while the informational content found on credit-market behavior has been

studied less. For example, Mclean & Zhao (2014) show that sentiment affects access to external finance. If changes in the credit-market sentiment capture the increase in future costs of credit, this should be reflected in the decrease in the leverage. An alternative notion is that the proposed sentiment captures an increase in the appeal of future investments, as predicted by Rognlie, Shleifer & Simsek (2018). Thus, a fall in both investments and the leverage can be explained by an increase in the cost of debt relative to the cost of equity; that is, by an inward shift in the supply of credit in a world in which the credit and equity markets are partially segmented.

To see whether the movements in the net debt and equity can be predicted by the proposed dispersion of beliefs measure, the top panel of Figure 8. displays monthly scatter plots of changes in net debt (left-hand side) and equity (right-hand side) issuance against the proposed credit-market sentiment. From these plots, one can gauge that the forecasted widening of credit spreads is associated with a subsequent leveraging – that is, an increase in debt and a decrease in equity issuance. The bottom panel of the same figure provides a visual representation of the relationship between the firms' issuing behavior and the beliefs in the beliefs-sorted quartile portfolios, also discussed in Table 2. This finding reinforces the results of the negative correlation between the debt and equity issuance, implying that share repurchases follow the rises in debt issuance as the latter financing is preferred to finance the former.

Table 3 formalizes these graphical relationships. Results report the findings from the second-step cross-sectional regressions (Equation 14) in which the changes in both net debt

issuance (NDI, Panel A) and net equity issuance (NEI, Panel B)³⁴ in year t – both scaled by assets at the year before $t-1$ – are regressed on the predicted changes in the credit-market sentiment estimated in Equation (13). Since Longstaff & Wang (2012) show that the expansions and contractions in the credit market are reactions to changes in agents' risk-sharing needs over economic cycles, the first control variable includes the ICS. This is added to determine whether the proposed credit sentiment captures additional information pertinent to firms' financing mix behavior when compared to the traditional macro sentiment measures. Other control variables include the monthly average number of Bloomberg's news sentiment measure (NEWS SENTIMENT), Bloomberg's estimates of analyst recommendations (ANALYST RECOMMENDATION), and analyst disagreement (ANALYST DISAGREEMENT) measure which is estimated as in Bali, Bodnaruk, Scherbina & Tang (2017). Macroeconomic control variables include the term spread (TERM SPREAD) and the default risk factor (DEF). Finally, the empirical test includes firm-specific market and balance sheet variables; these are firm's size measure (SIZE) – an inverse proxy for the expected cost of bankruptcy proxied as the log of total sales (Rajan & Zingales 1995)³⁵, the return on equity (ROE), the dividend payout ratio (DIVIDEND), firm stock returns (EQUITY RETURN), and the leverage ratio (LEVERAGE).

The results in Table 3 suggest that an elevated credit-market sentiment is associated with an increase in the net debt issuance. This finding confirms the initial insights gained

³⁴ NDI and NEI are estimated as $\frac{NDI}{A_{j,t-1}}$ and $\frac{NEI}{A_{j,t-1}}$, respectively, where NDI is the net debt issuance of firm j in month t , NEI is the net equity issuance of firm j in month t , and $A_{j,t}$ is the book value of total assets of firm j in month t .

³⁵ The choice of the log of total sales is used to conform to the existing, above mentioned literature. However, when for robustness, the alternative proxy for a firm's size – the log of market capitalization – is used, results remain generally consistent.

from Figure 8.. Although the coefficients of the beliefs dispersion decrease from 0.29 to 0.04, when all macro sentiment, attention, credit risk, and balance sheet control variables are pooled together in Model (4), the sentiment measure remains statistically significant. Beliefs appear to be an important economic factor for the financing mix. A one-standard-deviation positive shock in the daily credit-market sentiment (6.135) induces an increase in debt issuance of around 7% while the reduction in the net equity issuance appears negligible. These results suggest that, in the short-run, an elevated credit-market sentiment leads to an increase in the net debt issuance consistent with the credit-market optimism hypothesis of Bordalo, Gennaioli & Shleifer (2018). These results suggest that the measure of the proposed belief might capture the extrapolative beliefs of the investors in the market for credit risk, leading to an increase in credit issuance and investments, a hypothesis that is formally tested in Section 6.3.

Results relying on pooling all firm observations reveal a strong relationship between the uncertainty and firm-issuing behavior supporting the prediction of the asset pricing models with Epstein-Zin utility that allow the stochastic discount factor to depend on the future levels of risk. However, the proposed measure of the dispersion in beliefs in this article provides for different stochastic processes of fundamentals to drive different expectation formation rules. It is essential, therefore, to look at formation rules that govern individual behavior, thus addressing Lucas's critique.

Table 4 reports the findings from the second-step cross-sectional regressions (Equation 14) at the firm level. All regressions control for firm and month fixed effects, and the results report cluster-robust standard errors which account for within-cluster correlations not captured by the fixed effects estimator. Control variables are the same as in Table 3.

Results substantiate the findings reported in Table 3, evincing that a high firm-specific, credit-market sentiment is associated with an increase in the net debt issuance.

Next, since different leverage levels represent different “moneyness” of the put option implicit on a firm’s debt, the leverage has an increased value in times of high distressed periods for the firm with low expected growth rates and increased uncertainty. We, therefore, control for how a firm’s leverage interrelates with the dispersion of beliefs and perform the empirical analysis for different leverage levels separately. This approach also allows us to account for the “microfoundations” and confirm the robustness of the empirical regularities across different samples.

Table 5 contains the results. Results suggest that the dispersion in beliefs associates with a higher increase in debt issuance for all entities. This relationship is notably stronger for the deep-out-of-the-money entities – i.e. low-levered entities, and to a lesser extent for the at-the-money entities – i.e. high-levered entities. This finding is consistent with the notion that corporate leaders learning from the market’s past fears of crash risk extrapolate into higher credit issuance as a signal to the market. La Porta (1996), for example, shows that investors’ optimism about stocks with rapidly growing earnings, and pessimism about stocks with fading earnings, causes overvaluation of the former and undervaluation of the latter. The predictability of returns is, therefore, a result of the correction in expectations. Thus, it is the optimism that undervalues the credit risk and leads to an increase in capital issuance in the short run, as shown in our results. Table I.A.2, reported in the internet appendix, outlines the results of the positive relationship of expectations and the firm’s equity issuance, although this relationship is statistically insignificant.

6.3 Sentiment and investments

Studies in neuroscience show that our perceptions are influenced by our expectations built from the recent past. The Bayesian integration – a process whereby we combine our prior knowledge with uncertain evidence– affects our perceptions, thoughts, and actions.³⁶ In economics, expectations influence decisions and therefore take a central part in economic theory. Rognlie, Shleifer & Simsek (2018) theoretical model, for example, predicts that past investors' optimism induces an increase in the appeal for future investments.

Table 6 tests this prediction. The regressions are similar to Equation (14), with the dependent variable replaced with the ratio of total-investments-to-total-assets, and the additional control variable includes Tobin's Q. Results show that the importance of the credit-market sentiment for the investment activity is striking when different firm-specific sentiment proxies and firm-specific business risk factors are accounted for. However, once a firm's leverage and credit risk factors are considered, the coefficients of the sentiment drop and are insignificant. These results suggest that credit-market sentiment is positively related to firms investment behavior, although its economic importance is somewhat lower once the macroeconomic factors are accounted for. Restricting the analyses of investments behavior for the below-investment-grade credit-rated firms only (Table I.A.3 in the internet appendix) yields similar results.

These findings lay support to the “diagnostics expectations” predictions of (Bordalo, Gennaioli & Shleifer 2018, Bordalo, Gennaioli, Porta & Shleifer 2019) where the good news about fundamentals induces optimism at investors which then triggers expansion in credit supply and investments. Similar to Gennaioli, Ma & Shleifer (2016), beliefs are not

³⁶ See Sohn, Narain, Meirhaeghe & Jazayeri (20019) and Hermoso-Mendizabal, Hyafil, Rueda-Orozco, Jaramillo, Robbe & de la Rocha (2020), among others.

driven out by traditional business risk factors; this indicates an extrapolative nature of expectations and suggests that expectations deviate from Bayes' rule.

6.4 Sentiment and the cost of capital

Results showing the importance of the credit-market sentiment for the net credit issuance and investments warrant further investigation on the relation of the sentiment with the cost of debt. If changes in the credit-market sentiment predict an increase in the net debt issuance and investments, we should expect that buoyant credit-market sentiment should also relate to the changes in the cost of debt. Results reported in Table 7 suggest that shocks to the credit-market-implied sentiment measure signal an optimistic outlook on firms' prospects and thus a decrease in the cost of capital, although this relationship is statistically insignificant.

Restricting the analyses for below-investment-grade credit-rated entities (Table I.A.4 in the internet appendix) confirms these findings; changes in the credit sentiment are associated with a reduction in the cost of debt and an increase in the cost of equity, although these findings are not statistically significant.³⁷

Next, Table 8 reports the results of the effects of changes in the credit-market sentiment and changes in the corporate issuing behavior in the short term. It shows that changes in the credit-market sentiment are positively related to the changes in the short-term debt, although this relationship is statistically insignificant.³⁸ These results are consistent with the notion that unwinding of the past credit-market sentiment optimism about prospects

³⁷ Table I.A.5 in the internet appendix confirms this relationship for the equally-weighted quartile portfolios formed on firms' different leverage levels.

³⁸ Table I.A.6 in the internet appendix confirms this relationship for the equally-weighted quartile portfolios formed on firms' different leverage levels.

of the firm can lead to a lower effective debt financing and induce an increase in short-term debt issuance.

6.5 Endogeneity problem and robustness checks

The working hypothesis of this paper is that buoyant credit-market sentiment is related to the firm's financing mix decisions. One caveat on the findings of this paper has to do with the endogeneity problem; that is, the firm's financing mix decisions can also be driven by different firm fundamentals, which in turn can affect their credit conditions. This is a common issue in empirical corporate finance studies (Li 2016). The two-step procedure to imply credit-market based sentiment measure used in this paper resembles an instrumental variable approach that, to a certain degree, helps to mitigate this concern. This econometric approach controls for the possibility that the firms' financing and investments behavior are not merely a reflection of changes in the exogenous non-financial factors – which would be captured by forward-looking spreads estimated in the first-step regression. Furthermore, the regression specifications always account for firm and month fixed effects. Both these methods are found as useful econometric remedies in mitigating the endogeneity problem by Li (2016).

Next, additional results reported in the internet appendix, to save space, confirm the robustness of the empirical regularities across different samples; portfolios based on firms' different leverage levels or for sub-sample of below-investment credit-rated entities. Additional results reported in Table I.A.7 in the internet appendix explore the relation between the price reactions in the market for credit risk and the sentiment in the equity market. Regressing lagged realized volatility, realized jumps and cojumps on the news sentiment measure, as reported by Bloomberg, suggest that the past jumps based on credit-market

information predict a decline in the news sentiment, confirming the extrapolative nature in beliefs. This relation is consistent when lagged credit realized volatility, realized jumps and, cojumps are regressed on ICS with the coefficients of the risk factors being larger and still statistically significant. These results are available on request.

Finally, Table I.A.8 in the internet appendix reports results on the importance of the proposed credit-market sentiment on future economic activity. Consistent with the findings in Lopez-Salido, Stein & Zakrajsek (2017), and theoretical predictions of Bordalo, Gennaioli & Shleifer (2018), the credit-market sentiment is a statistically significant predictor of the future economic activity.

7. Conclusions

This paper assessed the belief formation rules of investors in the market for credit risk when under significant uncertainty and their implications for corporate decisions. Studies in psychology show that we base our personal beliefs on predictions of reward and cost, and these changes in views occur rapidly. Basing this study on high-frequency credit risk market information alone permits for a more accurate representation of the market's prevailing belief formation rules. The high-frequency trading based on machine learning algorithms allows for unbiased trading. Yet, these trading models are limited in predicting patterns when caught in rare events. In such circumstances, a credit analyst's judgment of future trends based on intuition and prior knowledge becomes crucial. The main result of this paper is that investors in the credit market overextrapolate and, therefore, biases documented in Greenwood & Hanson (2013) are also apparent in the high-frequency trading.

Results reported here show that beliefs are a market state variable, useful not only to predict future returns but also correlate with the risk factors and move with the moneyiness (leverage) levels. Furthermore, results suggest that the unwinding of past credit-market investors' optimism following extreme price movements in the credit spreads leads to an increase in firm debt issuance and investments supporting the notion that corporate leaders learn from asset prices.

We provide a psychological account for the Λ -shaped trading in the market for credit risk where belief formation rules, defined by extrapolation, are combined with the realization utility model, explained by cognitive dissonance.

This paper adds to a growing body of literature in behavioral finance that uses credit-market sentiment to study the credit cycles and real economic growth which includes the works of Bordalo, Gennaioli & Shleifer (2018), Lopez-Salido, Stein & Zakrajsek (2017) and Greenwood & Hanson (2013). We complement these studies by proposing a new method to imply the dispersion in beliefs in the credit market based on model-free unconditional variance estimates extracted from price data of diverse firms, providing analysts with an easy-to-compute approach on any day and a useful tool for countercyclical credit policies.

8. Tables and Figures

Fig. 1. Sentiment and Risk Factors

This figure plots the annualized Sharpe ratios of monthly credit returns of constant beliefs-sorted portfolios. The equally-weighted quartile portfolios are sorted on beliefs dispersion with 1 denoting the lowest dispersion of beliefs quartile (highest leverage levels) and 4 denoting the highest dispersion of beliefs quartiles portfolios (lowest leverage levels). The continuous line plots the unhedged Sharpe ratios and the dashed line plots the equity return delta-hedged Sharpe ratios. The estimation method of the beliefs proxy is discussed in Section 5. The sample runs from March 9, 2011, to December 10, 2016.

Fig. 2. Sentiment and changes in financing mix

The two top figures plots the average monthly relation between the corporate financing mix – net debt issuance $\left(\frac{\Delta NDI}{A_{j,t-1}}\right)$ and net equity issuance $\left(\frac{\Delta NEI}{A_{j,t-1}}\right)$ expressed as percent of book-value to total assets – and the credit-market dispersion of beliefs. *NDI* denotes net debt issuance of firm j in month t , *NEI* denotes net equity issuance of firm j in month t , and $A_{j,t}$ is the book value of total assets of firm j in month t . The left panel depicts the relation between the change in *NDI* and the sentiment while the right panel depicts the relation between the change in *NEI* and the sentiment. The bottom two figures plot the relationship of the *NDI* (left-hand-side) and the *NEI* (right-hand-side) and the quartile portfolios sorted on credit-market dispersion of beliefs measure. The equally-weighted portfolios are sorted on beliefs dispersion with 1 denoting the lowest and 4 denoting the highest dispersion of beliefs quartiles. The estimation method of the sentiment proxy is discussed in Section 5. The sample runs from March 9, 2011, to December 10, 2016.

Table 1 Summary statistics of credit risk measures

Panel A: Credit Risk Measures divided on S&P (Moody's) Credit Rating										
	AA		A		BBB		BB		All	
	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
CDS	88.372	91.071	89.440	80.627	89.875	94.206	92.004	96.908	89.923	90.703
RJV	0.177	0.410	0.261	1.209	0.232	0.797	0.167	0.349	0.232	0.890
AR(1)	0.12		0.22		0.28		0.30		0.23	
CoRJV									3.443	2.647
AR(1)									0.57	
λ	0.552	0.280	0.553	0.274	0.553	0.277	0.547	0.285	0.552	0.276
AR(1)	0.75		0.94		0.94		0.90		0.95	
N	4		28		51		13		96	
Panel B: Industry Sector										
	Industrial	Technology	Financial	Utilities	Energy	Basic Materials	Communications	Consumer Non-Cyclical	Consumer Cyclical	All
N	16	4	16	2	4	6	8	19	21	96

This table reports the summary statistics of credit spreads, and the credit risk measures: the Realized Jump Volatility (RJV), the market-wide cojumps (CoRJV) and the illiquidity measure λ . The AR(1) denotes first-order autocorrelation coefficients and N denotes the number of companies. The estimation procedure of the credit risk parameters is discussed in Section 5. Panel B reports the seven industry sectors from which the sampled firms come, and N as before denotes the number of companies. The sample runs from March 9, 2011, to December 10, 2016.

Table 2 Sentiment and CDS returns portfolio sorts

	RETURN	CDS	SENTIMENT	LEVERAGE	SIZE	NDI	NEI	α	t-stats
Low	-0.404	43.175	-0.069	0.517	8.764	0.197	0.101	-0.326	-8.57
2	-0.714	60.838	-0.031	0.494	8.679	0.412	0.001	-0.030	-0.56
3	-0.919	78.025	-0.001	0.495	8.554	0.219	-0.033	0.668	8.31
High	1.188	177.584	0.069	0.469	8.051	0.037	0.091	1.142	6.5

This table reports the monthly credit spread returns on equally-weighted quartile portfolios. Portfolios are constructed by sorting credit spreads each month on beliefs proxy, whose estimation method is discussed in Section 5. We then calculate the next month's equally-weighted portfolio returns, which are reported in column one. The second column reports the average portfolio CDS spreads. Columns three to five report the credit-market based dispersion of beliefs proxy SENTIMENT, the leverage ratio (the sum of current and long-term debt divided by the sum of total equity and current and long-term debt, LEVERAGE), and the firm size measure the log of total sales (SIZE). Columns six and seven report the net debt and equity issuance, NDI and NEI respectively. The last two columns report the five-factor alphas (denoted by α) and the 12 lags of Newey & West (1987) adjusted *t*-statistics of the alphas. The sample runs from March 9, 2011, to December 10, 2016.

Table 3 Sentiment and financing mix

	(1)	(2)	(3)	(4)
Panel A: Net debt issuance				
Δ SENTIMENT	0.245 (2.541)	0.293 (3.054)	0.294 (2.638)	0.044 (1.885)
Δ ICS		0.314 (2.462)	0.040 (0.314)	0.019 (1.496)
Δ NEWS SENTIMENT			0.051 (1.270)	-0.002 (-0.560)
Δ ANALYST RECOMMENDATIONS			0.043 (6.952)	0.005 (2.512)
Δ ANALYST DISAGREEMENT			0.001 (1.541)	-0.004 (-0.838)
Δ VIX				0.026 (0.365)
Δ SHORT RATE				-0.026 (-0.857)
Δ TERM SPREAD				0.003 (0.483)
Δ DEF				-0.127 (-1.789)
Δ SIZE				0.016 (1.070)
Δ EQUITY RETURN				0.157 (0.298)
Δ ROE				-0.000 (-0.170)
Δ LEVERAGE				-0.000 (-0.316)
R-squared	0.06	0.12	0.46	0.89
N	6258	6258	6258	6069
Panel B: Net equity issuance				
Δ SENTIMENT	0.001 (0.308)	0.001 (0.316)	0.001 (0.290)	0.001 (0.088)
Δ EQUITY SENTIMENT		0.000 (0.077)	0.002 (0.451)	-0.002 (-0.235)
Δ NEWS SENTIMENT			-0.002 (-0.988)	-0.002 (-0.676)
Δ ANALYST RECOMMENDATIONS			0.000 (0.193)	0.000 (0.230)
Δ ANALYST DISAGREEMENT			0.000 (0.142)	0.004 (0.583)
Δ VIX				0.567 (1.357)
Δ SHORT RATE				0.077 (1.459)
Δ TERM SPREAD				0.088 (3.276)
Δ SIZE				-0.000 (-0.184)
Δ EQUITY RETURN				-0.786 (-1.822)
Δ ROE				0.000 (0.073)
Δ LEVERAGE				0.001 (0.149)
R-squared	0.00	0.00	0.01	0.34
N	6258	6258	6258	6229

This table reports the regressions of changes in financing mix and the sentiment with the clustered standard errors at the firm level. The dependent variables are changes in the net debt issuance in Panel A and changes in net equity issuance in Panel B, regressed on changes in the credit-market sentiment (estimation procedure discussed in Section 5.) and a set of other firm-specific sentiment and attention proxies; namely, the Michigan Index of Consumer Sentiment (ICS), Bloomberg's news sentiment (NEWS SENTIMENT), Bloomberg's estimates of ANALYST RECOMMENDATIONS ratings scales between '1' and '5' where return of '5' is the strongest ranking (buy or similar), whereas a return of '1' is the weakest (sell or similar), ANALYST DISAGREEMENT which is estimated as in Bali, Bodnaruk, Scherbina & Tang (2017): the standard deviation of earnings forecasts divided by the absolute value of the mean earnings' forecasts as reported by Bloomberg (ANALYST DISAGREEMENT), the returns of the VIX Index, SHORT RATE, TERM SPREAD, DEF, SIZE, firm stock returns (EQUITY RETURN), ROE, and LEVERAGE. The intercepts are estimated but not reported. *t*-statistics are in parentheses. Δ denotes the first-difference in variables. The sample runs from March 9, 2011, to December 10, 2016.

Table 4 Sentiment and financing mix firm-level data

	(1)	(2)	(3)	(4)
Panel A: Net debt issuance firm-specific				
Δ SENTIMENT	0.046 (2.046)	0.045 (2.010)	0.041 (1.800)	0.040 (1.727)
Δ ICS		0.017 (1.450)	0.019 (1.561)	0.018 (1.440)
Δ NEWS SENTIMENT			-0.002 (-0.495)	-0.002 (-0.461)
Δ ANALYST RECOMMENDATIONS			0.005 (2.519)	0.005 (2.497)
Δ ANALYST DISAGREEMENT			-0.000 (-0.202)	-0.004 (-0.884)
Δ VIX				0.008 (0.112)
Δ SHORT RATE				-0.026 (-0.851)
Δ TERM SPREAD				0.003 (0.595)
Δ DEF				-0.121 (-1.728)
Δ SIZE				0.017 (1.123)
Δ EQUITY RETURN				0.114 (0.217)
Δ ROE				-0.001 (-0.200)
Δ LEVERAGE				0.029 (2.050)
R-squared	0.00	0.00	0.00	0.00
N	6258	6258	6258	6229
Panel B: Net equity issuance firm-specific				
Δ SENTIMENT	0.018 (1.580)	0.018 (1.594)	0.018 (1.619)	0.014 (1.263)
Δ ICS		-0.003 (-0.608)	-0.003 (-0.436)	-0.003 (-0.543)
Δ NEWS SENTIMENT			-0.001 (-0.432)	-0.001 (-0.359)
Δ ANALYST RECOMMENDATIONS			-0.000 (-0.395)	0.000 (0.124)
Δ ANALYST DISAGREEMENT			0.000 (0.220)	0.002 (0.926)
Δ VIX				-0.105 (-3.025)
Δ SHORT RATE				-0.029 (-1.885)
Δ TERM SPREAD				0.001 (0.227)
Δ DEF				-0.011 (-0.316)
Δ SIZE				0.029 (3.904)
Δ EQUITY RETURN				0.231 (0.890)
Δ ROE				0.002 (1.226)
Δ LEVERAGE				0.010 (1.426)
R-squared	0.00	0.00	0.00	0.01
N	6258	6258	6258	6229

This table reports the results of the regressions on firm-level data of changes in financing mix and the sentiment (estimation procedure discussed in Section 5.) Panel A reports the results of changes in net debt issuance ($NDI/A_{j,t-1}$) and Panel B reports the results of changes in net equity issuance ($NEI/A_{j,t-1}$) on sets of regressors defined as in Tables 2 and 3. Dependent variables are the same as in Table 3. The intercepts are estimated but not reported. Δ denotes the first-difference in variables. Robust t -statistics, clustered at firm level, are in parentheses. The sample runs from March 9, 2011, to December 10, 2016.

Table 5 Sentiment and net debt issuance– leverage portfolios

	Leverage Groups							
	<25%				25-50%			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Δ SENTIMENT	0.025 (1.959)	0.024 (1.896)	0.019 (1.644)	0.028 (2.249)	0.045 (1.165)	0.046 (1.181)	0.048 (1.236)	0.047 (1.185)
Δ ICS		-0.017 (-1.000)	-0.020 (-1.180)	-0.009 (-0.597)		0.016 (0.481)	0.020 (0.591)	0.029 (0.794)
Δ NEWS			0.006 (1.690)	0.006 (1.845)			0.003 (1.181)	0.003 (1.048)
Δ ANALYST RECOMMENDATIONS			0.005 (1.588)	0.004 (1.389)			-0.004 (-0.995)	-0.004 (-0.931)
Δ ANALYST DISAGREEMENT			-0.001 (-1.065)	-0.002 (-1.098)			-0.002 (-1.499)	-0.003 (-1.569)
Δ VIX				0.142 (1.685)				0.015 (0.199)
Δ SHORT RATE				-0.057 (-0.848)				-0.082 (-1.896)
Δ TERM SPREAD				0.001 (0.130)				-0.002 (-0.364)
Δ DEF				-0.093 (-2.193)				0.003 (0.040)
Δ SIZE				-0.006 (-0.464)				0.030 (0.511)
Δ EQUITY RETURN				-0.271 (-0.539)				0.649 (1.069)
Δ ROE				-0.058 (-1.048)				0.018 (0.391)
Δ DIVIDEND				0.000 (0.690)				-0.000 (-0.696)
R-squared	0.00	0.00	0.01	0.02	0.00	0.00	0.01	0.01
N	1624	1624	1624	1604	1614	1614	1614	1549

	50-75%				>75%			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Δ SENTIMENT	0.000 (0.002)	-0.001 (-0.067)	0.003 (0.172)	0.007 (0.363)	0.127 (1.396)	0.132 (1.407)	0.096 (1.759)	0.102 (1.844)
Δ ICS		-0.021 (-1.027)	-0.021 (-1.009)	-0.034 (-1.540)		0.110 (1.553)	0.082 (2.332)	0.099 (2.242)
Δ NEWS			-0.006 (-1.499)	-0.008 (-1.740)			0.001 (0.094)	0.003 (0.537)
Δ ANALYST RECOMMENDATION			-0.004 (-1.310)	-0.003 (-1.190)			0.019 (0.659)	0.019 (0.645)
Δ ANALYST DISAGREEMENT			0.005 (0.345)	0.003 (0.238)			-0.000 (-0.723)	-0.010 (-1.331)
Δ VIX				-0.113 (-1.238)				0.090 (0.408)
Δ SHORT RATE				0.083 (1.640)				-0.086 (-0.750)
Δ TERM SPREAD				-0.005 (-0.681)				0.022 (0.702)
Δ DEF				-0.272 (-3.002)				-0.195 (-1.035)
Δ SIZE				0.039 (1.773)				-0.017 (-0.256)
Δ EQUITY RETURN				1.033 (1.841)				-0.911 (-0.639)
Δ ROE				0.065 (1.647)				-0.001 (-0.863)
Δ DIVIDEND				0.000 (0.333)				-0.000 (-0.097)
R-squared	0.00	0.00	0.00	0.02	0.00	0.00	0.01	0.01
N	1635	1635	1635	1580	1385	1385	1385	1336

This table reports the results of equally-weighted quartile portfolios sorted on firms leverage. The regressions are run on the changes in net debt issuance on the credit sentiment and a set of regressors defined as in Tables 2 and 3. The intercepts are estimated but not reported. Δ denotes the first-difference in variables. Robust t -statistics, clustered at firm level, are in parentheses. The sample runs from March 9, 2011, to December 10, 2016.

Table 6 Sentiment and investments

	(1)	(2)	(3)	(4)	(5)
Δ SENTIMENT	29.772 (3.708)	28.700 (3.527)	27.503 (3.422)	26.900 (3.318)	6.255 (1.279)
Δ ICS		7.838 (0.857)	13.226 (1.328)	14.680 (1.461)	1.657 (0.289)
Δ NEWS SENTIMENT			-5.514 (-1.637)	-5.205 (-1.521)	-1.786 (-0.945)
Δ ANALYST			1.195 (1.940)	1.400 (2.183)	0.348 (1.042)
Δ ANALYST DISAGREEMENT			-2.690 (-0.273)	-6.628 (-0.644)	-0.559 (-0.127)
Δ TOBINQ				1.032 (0.591)	0.599 (0.602)
Δ REAL SALES				-0.000 (-0.156)	-0.000 (-0.785)
Δ EQUITY RETURN				-1053.695 (-1.529)	-237.287 (-0.652)
Δ VIX					116.452 (0.712)
Δ SHORT RATE					2.592 (0.177)
Δ TERM SPREAD					1.905 (0.272)
Δ LEVERAGE					-1.965 (-0.602)
Δ DIVIDEND					-0.265 (-2.907)
R-squared	0.12	0.13	0.18	0.20	0.18
N	6565	6565	6565	6565	6079

This table reports the results of changes in total-investments-to-total-assets ratio on predicted changes in credit-market sentiment whose estimation method is discussed in Section 5. Additional control variables to those reported in Table 3 include changes in Tobin's Q (TOBIN'S Q) and changes in the firm's real sales (REAL SALES). The intercepts are estimated but not reported. Standard errors are clustered at the firm level and the *t*-statistics are reported in parentheses. Δ denotes the first-difference in variables. The sample runs from March 9, 2011, to December 10, 2016.

Table 7 Sentiment and cost of capital firm-specific data

	(1)	(2)	(3)	(4)
Panel A: Cost of debt firm-specific				
Δ SENTIMENT	-0.075 (-1.246)	-0.076 (-1.252)	-0.075 (-1.245)	-0.078 (-1.219)
Δ ICS		0.013 (0.429)	0.005 (0.144)	0.001 (0.031)
Δ NEWS SENTIMENT			0.009 (0.968)	0.009 (0.950)
Δ ANALYST RECOMMENDATIONS			-0.004 (-0.619)	-0.003 (-0.492)
Δ ANALYST DISAGREEMENT			-0.000 (-0.201)	-0.023 (-1.914)
Δ VIX				0.166 (0.841)
Δ SHORT RATE				0.294 (3.41)
Δ TERM SPREAD				0.287 (5.417)
Δ DEF				0.044 (0.233)
Δ SIZE				0.009 (0.239)
Δ EQUITY RETURN				0.230 (0.160)
Δ ROE				0.002 (0.307)
Δ DIVIDEND				-0.002 (-1.460)
R-squared	0.16	0.16	0.16	0.17
N	6565	6565	6565	6079
Panel B: Cost of equity firm-specific				
Δ SENTIMENT	-0.396 (-2.193)	-0.399 (-2.211)	-0.397 (-2.198)	-0.429 (-2.265)
Δ ICS		0.104 (1.163)	0.085 (0.917)	0.084 (0.879)
Δ NEWS SENTIMENT			0.020 (0.722)	0.021 (0.738)
Δ ANALYST			-0.017 (-1.022)	-0.021 (-1.162)
Δ ANALYST DISAGREEMENT			-0.003 (-0.576)	-0.088 (-2.510)
Δ VIX				0.287 (2.07)
Δ SHORT RATE				0.925 (3.831)
Δ TERM SPREAD				1.378 (8.762)
Δ DEF				0.729 (1.312)
Δ SIZE				-0.069 (-0.601)
Δ EQUITY RETURN				-3.716 (-0.870)
Δ ROE				-0.014 (-0.729)
Δ DIVIDEND				-0.010 (-2.028)
R-squared	0.12	0.12	0.12	0.12
N	6565	6565	6565	6079

This table reports the results of changes in firms' cost of capital on predicted changes in credit-market sentiment whose estimation method is discussed in Section 5. Panel A reports the results of changes in the after-tax cost of debt on the credit sentiment and Panel B reports the results of regressions of changes in cost of equity on the credit-market sentiment. Other covariates are defined as in Tables 2 and 3. The intercepts are estimated but not reported. Δ denotes the first-difference in variables. Robust t -statistics, clustered at firm level, are in parentheses. The sample runs from March 9, 2011, to December 10, 2016.

Table 8 Sentiment and changes in short-term debt firm-specific data

	(1)	(2)	(3)	(4)
Δ SENTIMENT	4.453 (0.038)	3.276 (0.028)	10.364 (0.088)	1.505 (0.012)
Δ ICS		25.880 (0.423)		
Δ VIX			36.382 (0.106)	-249.208 (-0.639)
Δ SHORT RATE			35.244 (0.225)	-23.397 (-0.137)
Δ TERM SPREAD			-23.318 (-0.818)	-21.925 (-0.718)
Δ DEF			90.271 (0.248)	137.315 (0.355)
Δ SIZE				97.353 (1.193)
Δ EQUITY RETURN				-5121.362 (-1.781)
Δ ROE				-0.274 (-0.019)
Δ DIVIDEND				7.023 (1.977)
R-squared	0.00	0.00	0.00	0.00
N	6565	6565	6565	6079

This table reports the results of the predictive regressions on firm-level data of changes in short-term debt and the sentiment (estimation procedure discussed in Section 3 of the paper). Covariates are defined as in Tables 2 and 3. The intercepts are estimated but not reported. Standard errors are clustered at the firm level and the robust t -statistics are reported in parentheses. Δ denotes the first-difference in variables. The sample runs from March 9, 2011, to December 10, 2016.

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