

Credit Ratings and Investments*

Anna Bayona Oana Peia Razvan Vlahu

October 2025

Abstract

We study the impact of potentially inflated credit ratings in bond markets using experimental coordination games. Theoretical models featuring a feedback effect between capital markets and the real economy suggest that inflated ratings can have both positive and negative effects. Comparing markets with and without a credit rating agency, we find that ratings significantly influence investor behaviour and capital allocation to firms. While we find evidence for both positive and negative real effects of potentially inflated ratings, the presence of a rating has an overall positive effect. We examine the mechanisms underlying these real effects, and find that they operate mainly through investors' beliefs about others' behaviour, and less so through beliefs about the firm's fundamentals.

JEL: D81; D82; D83; G24

Keywords: Credit ratings; Imperfect information; Investor beliefs; Firm financing

*Bayona: ESADE Business School, Universitat Ramon Llull, e-mail: anna.bayona@esade.edu; Peia: University College Dublin, School of Economics, e-mail: oana.peia@ucd.ie; Vlahu: De Nederlandsche Bank, Financial Stability Division, e-mail: r.e.vlahu@dnb.nl. We thank Dion Bongaerts, Martin Brown, Andrea Colciago, Camille Cornand, Vessela Daskalova, John Duffy, Lorenz Emter, Rustamdjan Hakimov, Frank Heinemann, Stefan Hirth, Anita Kopanyi-Peuker, Rosemarie Nagel, Mikael Paaso, Luba Peterson, Margaret Samahita, Spyros Terovitis, Stefan Trautmann, Radu Vranceanu, and Sweder van Wijnbergen, as well as seminar and conference participants at University of Innsbruck, Nottingham Business School, University of Piraeus, DNB, ESADE, University College Dublin, the 12th Workshop on Theoretical and Experimental Macroeconomics (Berlin), the 12th International Conference of the French Association of Experimental Economics (Lyon), the 8th ERMAS conference (Cluj-Napoca), CREST/LESSAC Workshop in Experimental Economics (Dijon), the 6th Stavanger Behavioural Economics and Finance Workshop, ICMAIF (Crete), IBEFA (San Diego), EEA (Barcelona), the Strategic Interaction in Corporate Finance Workshop (Aarhus), and the Economic Sciences Association (Exeter) for valuable comments and suggestions. We also thank Fatih Cingöz, Ji Ho Choi, Pablo López-Aguilar, Sergio Salas, Néstor Salcedo and Konstantina Zacharaki for excellent research assistance. Bayona acknowledges the financial support from the Spanish Ministry of Science, Innovation and Universities and Agencia Nacional de Investigación (Grants: PGC2018-098670 and PID2024-156339NA-I00) financed by FEDER and EU and Universitat Ramon Llull (Grant: 2021-URL-Proj-068). The views expressed in this paper are those of the authors and do not necessarily represent those of DNB or the Eurosystem.

1 Introduction

The feedback effects between capital markets and the real economy are often understated. Credit ratings play a pivotal role in this intricate relationship, as they do not merely reflect firms' creditworthiness, but also affect it (Manso, 2013). They do so by shaping investors' decisions on where to allocate their capital, subsequently affecting access to credit and the associated borrowing costs.

Yet, the 'issuer-pays' business model used by the leading credit rating agencies (CRAs) has raised concerns about potential rating inflation (i.e., instances when a CRA may overestimate a firm's creditworthiness), which could result in adverse effects on the functioning of the feedback mechanism between financial markets and the real economy.¹ The potential consequences of inflated credit ratings can be significant. They promote capital misallocation, distortion of market prices, and a false sense of security for investors.² Investors may be lured into taking on more risk than they can handle, while issuers may be able to access cheaper funding than they deserve. Inflated credit ratings can also lead to moral hazard problems with adverse real economic effects, where issuers take on more risk than they otherwise would. At the same time, inflated ratings can also foster market liquidity and facilitate firms' access to credit markets, which can benefit economic growth, particularly when improved financing conditions enable efficient investments. Understanding the role that inflated ratings play in shaping investors' behaviour and decision-making is empirically challenging, as it is difficult to establish the causal impact of ratings on investors' or firms' decisions, particularly in environments where multiple equilibria may be present (Boot *et al.*,

¹See, for example, Ashcraft and Schuermann (2008), Jiang *et al.* (2012), Alp (2013), Cornaggia and Cornaggia (2013), White (2013), and Fulghieri *et al.* (2014). Factors that can lead to credit inflation include conflicts of interest, such as the desire to maintain a good relationship with an issuer (Mählmann, 2011; He *et al.*, 2012; Strobl and Xia, 2012; Frenkel, 2015); (lax) regulation (Opp *et al.*, 2013; Bae *et al.*, 2015); the pressure to retain market share (Becker and Milbourn, 2011; Bolton *et al.*, 2012; Baghai and Becker, 2020); or ratings-shopping (Skreta, 2009; White, 2010; Bongaerts *et al.*, 2012).

²During the Global Financial Crisis, large losses on highly-rated securities and their downgrades indicated that these securities had inflated ratings (US Senate, 2007; Benmelech and Dlugosz, 2009a,b; Griffin and Tang, 2011, 2012; US Government, 2011; Griffin *et al.*, 2013). Major rating agencies, such as Moody's and Standard & Poor's, paid more than \$1 billion in legal settlements to resolve allegations arising from their role in providing inflated ratings to mortgage-related securities in the run-up to the financial crisis.

2006)).³ In this paper, we design a laboratory experiment that allows us to overcome some of these challenges by providing an ideal environment to study investors' reactions to inflated ratings.

We provide evidence on the informational role of (potentially) inflated credit ratings and their impact on investment decisions. We adapt Goldstein and Huang's (2020) bond financing model to derive predictions that guide our experimental design. A firm can invest in two types of risky projects: low-risk or high-risk. To undertake a project, the firm uses two sources of financing: internal funds from ongoing activities and external financing from the bond market. The low-risk project has a higher net present value than the high-risk project but requires a larger investment due to its scarcity and associated cost of screening. If the firm cannot secure enough funds to undertake the efficient, low-risk project, it can either invest in a high-risk project or default. Default occurs in the model whenever external funds are insufficient to cover the firm's losses from existing activities.

The firm raises external financing from investors who receive noisy private signals about the firm's internal funds (representing its fundamentals). Additionally, these investors may observe a publicly available credit rating. A forward-looking CRA perfectly observes the firm's fundamentals and assesses its creditworthiness by assigning either a good (potentially inflated) or a bad (perfectly revealing) rating.⁴ A credit rating is inflated when the rating agency pools high- and low-risk firms together by giving them a good rating, thus not accurately reflecting the true quality of high-risk firms. Nevertheless, such a rating conveys positive information about a firm by signaling lower default risk, attracting more investors to buy bonds. The resulting increased availability of external financing, in turn, influences the firm's project choice. The model allows for positive and negative real effects of inflated ratings, depending on parametrization. A positive real effect occurs when a firm that would

³While several studies document a positive correlation between changes in ratings and firms' and investors' decisions, these studies often face an endogeneity problem, as it is difficult to causally show that investors react to the change in rating itself and not some underlying firm fundamental that is observed by both investors and the rating agency (Cornaggia *et al.*, 2018).

⁴A firm receives a good rating when its internal funds are above a specific (default) threshold. When deriving the threshold, the rating agency considers the effect of the rating on investors' and the firm's decisions.

have chosen a high-risk project in the absence of a credit rating instead undertakes a low-risk project due to improved access to finance. Conversely, a negative real effect emerges when a firm that would otherwise have defaulted in the absence of the rating gambles for resurrection by investing in the inefficient high-risk project.

We design a laboratory experiment that allows us to evaluate these two opposing effects while controlling for investors' information sets and firm fundamentals. In the experiment, participants act as investors tasked with deciding whether to purchase or not a firm's bond. They play a five-person coordination game where their payoffs from investing depend on whether the firm undertakes the low- or high-risk project or defaults. The firm's decision is mechanical and depends on the number of investors financing the firm and the firm's fundamentals.⁵ Before participants make their investment decision, they receive a noisy private signal about the firm's fundamentals (i.e., internal funds). We then elicit participants' beliefs about the true value of fundamentals and how many investors buy the bonds. We consider two treatments in a between-subject design: (i) a Baseline treatment, where subjects only receive the private signal, and (ii) a CRA treatment, where subjects observe a (potentially inflated) public credit rating about the firm's ability to repay its creditors in addition to the private signal. In the CRA treatment participants are not explicitly informed that the rating may be inflated. Similar to the firm's decision, the rating is computerized and automatically determined according to the theoretical model's predictions. Based on the model's predictions, we derive several testable hypotheses regarding the positive and negative effects of inflated ratings for different levels of firm fundamentals.

We find that the firm's access to external finance differs significantly across the two treatments, conditional on firm fundamentals and the observed rating. First, firms in the CRA treatment with relatively high (low) fundamentals receive substantially more (less) external financing than firms with similar fundamentals in the Baseline treatment. Second, observing (potentially) inflated good ratings induces more investors to buy the firm's bonds. This

⁵This experimental design allows us to focus on participants' decision-making while shutting down the possibility for firm strategic behaviour.

facilitates greater investment in low-risk projects (a positive real effect) but also enables some firms that would otherwise have defaulted to undertake high-risk projects (a negative real effect). At the same time, we document a strong effect of observing a bad rating. In the Baseline treatment, the absence of a public rating leads to greater investment in firms with weak fundamentals, resulting in more firms receiving sufficient funds to pursue high-risk projects. In contrast, in the CRA treatment, lower investment in weak firms leads to more defaults rather than the undertaking of high-risk projects, complementing the positive real effect of good ratings. Overall, across all levels of firm fundamentals, the positive effects dominate: the treatment with a public rating results in significantly fewer high-risk projects.

To understand the mechanisms underlying these results, we study individual investment behaviour and analyze the effects of credit ratings on investors' actions and beliefs. Our results suggest that ratings act as strong coordination devices. Investors in the CRA treatment who observe a good (bad) rating are more (less) likely to buy the firm's bonds than investors in the Baseline treatment. The mechanism operates as follows. Following a good (potentially inflated) rating, investors hold significantly higher beliefs about the number of others investing and display overoptimism about fundamentals. This strengthens coordination on investment and, in a setting with feedback effects between financial and real sectors, leads to more efficient firm investment and improved credit quality for some firms. At the same time, a good rating enables firms with weak fundamentals to gamble for resurrection by pursuing high-risk projects. By contrast, a bad rating induces investors to coordinate on not investing, driven partly by lower expectations about fundamentals, but especially by the belief that others will not invest. This reduces external funding for weak firms and curtails their risky investment. Taken together, when ratings may be inflated, both good and bad ratings enhance coordination in ways that amplify positive real outcomes, underscoring the powerful role of public signals in shaping individual investment decisions and firm outcomes. Moreover, the rating acts as a strong focal point, enabling coordination around both good and bad ratings. This mechanism explains why we observe an overall positive effect of inflated ratings: in the Baseline treatment, the absence of such a focal point leads to excessive

investment in defaulting firms.

Our paper relates to several strands of the literature. There is a rich theoretical literature on the real effects of financial markets (see [Bond *et al.*, 2012](#); [Goldstein, 2023](#), for reviews), with several works specifically focusing on the real effects of credit ratings ([Boot *et al.*, 2006](#); [Jeon and Lovo, 2013](#); [Manso, 2013](#); [Hirth, 2014](#); [Goel and Thakor, 2015](#); [Fulghieri *et al.*, 2014](#); [Sangiorgi and Spatt, 2017](#); [Donaldson and Piacentino, 2018](#); [Daley *et al.*, 2020](#); [Parlour and Rajan, 2020](#); [Terovitis, 2020](#)). Our empirical results are consistent with the theoretical predictions from [Boot *et al.* \(2006\)](#), who show that credit ratings can serve as coordination mechanisms.

Second, our paper relates to the empirical literature that attempts to identify the causal effects of ratings on investors' decisions. Several papers exploit various exogenous changes in firms' ratings that are unrelated to fundamentals (e.g., rating refinements or automatic rating downgrades due to sovereign risk) to overcome the endogeneity concern that the change in rating and the change in investors' behaviour can be driven by the same (unobserved) confounding factors (see, for example, [Kliger and Sarig, 2000](#); [Kisgen, 2009](#); [Tang, 2009](#); [Sufi, 2009](#); [Bannier and Hirsch, 2010](#); [Kisgen and Strahan, 2010](#); [Ellul *et al.*, 2011](#); [Almeida *et al.*, 2017](#); [Cornaggia *et al.*, 2018](#)).⁶ However, this literature cannot assess the informational role of *inflated* ratings, as one cannot empirically observe which ratings are inflated. Using a laboratory experiment allows us to overcome this obstacle and study the informational channels through which rating inflation can affect investors' decisions and market outcomes. While laboratory experiments, by their nature, have limitations in generalizing findings to broader contexts, the same is true for any empirical study in a specific institutional setting. Various factors, including portfolio structure, household wealth, and financial sophistication, influence investment decisions in the bond market. However, our goal is not the prediction of quantitative effects. Instead, our focus is on gaining a deeper understanding of the fundamental mechanisms at play when public information impacts investment

⁶This literature finds that CRAs' actions affect market participants and have real effects on firms' access to capital and their investments.

behaviour within an environment of strategic uncertainty. The evidence suggests that such qualitative behavioural mechanisms identified in laboratory experiments generalize to non-student populations ([Huck and Muller, 2012](#); [Noussair *et al.*, 2014](#)) and even professionals ([Frechette, 2015](#); [Weitzel *et al.*, 2020](#)). As [Levy \(1994\)](#) argues, experimental participants create their own frame of mind in which they make decisions for modest stakes in the same way they would make decisions outside the laboratory for significant stakes.

Third, our work adds to an expanding experimental finance literature (see [Sunder, 2007](#); [Bossaerts *et al.*, 2009](#); [Bloomfield and Anderson, 2010](#), for reviews). Within this literature, there are a few experimental studies on credit ratings. [Keser *et al.* \(2017\)](#) study the repeated interaction between an issuer and a CRA and find that issuers frequently request ratings, while the CRA reciprocates with rating inflation. [Rabanal and Rud \(2017\)](#) show how market structure affects credit ratings. In contrast to these papers, we study the effect of a credit rating on investors' decisions. Importantly, in our experiment, participants play the role of investors who decide whether to buy the firm's bond, while the decisions of the firm and the rating agency are based on their optimizing behaviour. Our paper is the first to empirically study the economic efficiency of inflated ratings when there is a feedback effect between the real economy and the financial sector. In this aspect, our work relates to [Weber *et al.* \(2018\)](#), who study the feedback effect between a bond's initial public offering price and the probability of issuer default.

Finally, we add to a rich experimental global games literature that studies participants' reactions to private and public information in contexts of strategic complementarities. Several papers, including [Heinemann *et al.* \(2004\)](#), [Cabrales *et al.* \(2007\)](#), and [Cornand and Heinemann \(2014b\)](#), find that participants tend to overreact to public information with public signals acting as focal points. Public signals bear important welfare implications that depend on the optimal level of social coordination ([Cornand and Heinemann, 2014a](#)). [Gao \(2008\)](#) emphasizes the benefits of transparency in an experimental design based on [Allen *et al.* \(2006\)](#), and shows that public information in the form of accounting disclosure leads to market efficiency by driving market prices close to fundamental values. [Sanjay and Maier](#)

(2016) study the role of the precision of public information on coordination failures and find that granular disclosure increases participants’ strategic uncertainty, which, in turn, increases the likelihood of coordination failure. We complement this literature by showing how a public credit rating affects the allocation of capital and market outcomes in the presence of feedback effects between public signals and the real economy.

Our paper is structured as follows. Section 2 presents a simple model of credit ratings and investments and formulates the empirical hypotheses. Section 3 describes the experimental design and procedures. Section 4 shows our results. Section 5 concludes.

2 Theoretical framework, predictions and hypotheses

We sketch a simplified theoretical framework that adapts the model of Goldstein and Huang (2020) to derive theoretical predictions and hypotheses that guide our experimental design. In particular, we streamline two dimensions of Goldstein and Huang (2020). First, we simplify the firm’s liabilities and financing structure by focusing on the size of funding available to the firm and, to a lesser extent, on the financing cost. Second, we use a uniform distribution for fundamentals and signals instead of a common improper prior for fundamentals and a normal distribution. Our predictions show that the essence of the results of Goldstein and Huang (2020) carry over in this simplified setting that we consider.⁷

2.1 Framework

We consider an economy consisting of a continuum of investors endowed with wealth w , a credit rating agency, and a firm that raises financing from the bond market. There are three dates $(0, 1, 2)$, no discounting and all agents are risk-neutral. The timing of the game is as follows. At $t = 0$, the CRA assigns a credit rating to the firm (the issuer). Investors observe a private signal about the firm’s fundamentals and, potentially, a credit rating. Each investor

⁷While our framework uses Goldstein and Huang (2020) to derive predictions, our main goal is to study the mechanisms driving investor behaviour in response to the observed information signals. These aspects are not the primary focus of their paper’s theoretical framework.

then decides whether or not to buy the firm's bonds. At $t = 1$, the firm chooses whether to default or invest in a new risky project based on its available funds. If the firm invests, the cash flow is realized at $t = 2$, and bondholders are repaid in full whenever the firm is solvent.

Projects

The firm is endowed with an ongoing project and has two additional investment opportunities: a low-risk project (LR) and a high-risk project (HR). The ongoing project produces θ , at date 0, which is drawn from a uniform distribution over $[\underline{\theta}, \bar{\theta}]$, with $\underline{\theta} < 0 < \bar{\theta}$, and represents the firm's fundamentals (internal funds). The LR project generates the following distribution of cash flows at date 2: $V > 0$ with probability $p \in (0, 1)$, and 0 with probability $1 - p$. Analogously, the HR project produces $H > V$ with probability q , and 0 with probability $1 - q$, where $0 < q < p$. The firm can also default at $t = 1$ and its liquidation value is L . Following [Goldstein and Huang \(2020\)](#), we assume that the firm's expected cash flows are ranked as follows: $pV > L > qH$. The fact that LR (HR) projects have higher (lower) expected cash flows than the firm's liquidation value allows us to generate predictions about the positive and negative implications of ratings. The firm's investment choice is unobservable and unverifiable.

The firm needs a certain amount of funding to undertake a new project. We assume that the LR-type of projects are in short supply and can be uncovered through costly screening efforts. The LR project requires a higher initial investment (including screening costs), I , with $I \geq \bar{\theta}$, whereas the HR project can be undertaken with a smaller investment, $i < I$.⁸ For simplicity, we set $i = 0$. We also assume that the LR project has a higher net present value: $pV - I > qH$.

Funding

The firm has two sources of financing: its own internal funds from the ongoing project, θ , representing the firm's fundamentals, and external funds from capital markets. The firm may need to raise external funds not only to undertake a new project but also to cover any

⁸This specification is consistent, for example, with the idea of higher entry costs required for access to LR projects, where entry costs may be thought of as a combination of transaction and informational costs.

losses from the ongoing project.⁹ If the firm's available funds at $t = 1$ are less than 0, it defaults, and creditors who financed the firm (if any) lose their investment. The firm's payoff in case of default is also zero, as any liquidation value L is lost in the bankruptcy procedure.

External financing is obtained from investors in the bond market. The firm issues zero-coupon bonds with face value F , with $1 < F < I$, at price B , with $1 \leq B < F$.¹⁰ The bonds mature at $t = 2$. If the firm does not default at date 1 and the new project is successful, bondholders are fully repaid at date 2.¹¹ Conversely, when the risky investment returns 0, the firm is insolvent and its creditors receive nothing because of bankruptcy costs. We also assume that

$$qF < B < pF, \quad (1)$$

so that investors buy the bond when they know that the firm invests in the LR project, but not when the firm invests in the HR project or defaults at $t = 1$. Combining the two sources of funds, the total amount of financing available to the firm, $K(\theta)$, is

$$K(\theta) = \theta + W(\theta)B, \quad (2)$$

where we denote by $W(\theta)$ the mass of investors that buy the firm's bond at price B . The firm's expected payoff is as follows:

$$\begin{cases} p[V - I + K(\theta) - W(\theta)F] & \text{if the firm invests in LR project} \\ q[H + K(\theta) - W(\theta)F] & \text{if the firm invests in HR project} \\ 0 & \text{if the firm defaults at } t = 1. \end{cases} \quad (3)$$

Specifically, when available funds are large enough (i.e., $K(\theta) \geq I$) and the firm invests in the LR project, its net profit is, with probability p , the return on the LR project net of investment

⁹Note that since the ongoing project may generate losses, the problem of raising capital remains relevant even when the investment cost of the HR project i equals zero.

¹⁰Since our focus is on the effect of credit ratings on the amount of bonds raised rather than their price, we follow [He and Xiong \(2012\)](#) and [Goldstein and Huang \(2020\)](#) in assuming that both the face value and the price of the bond are exogenously given. We further impose $w = B$, ensuring that each investor purchases exactly one bond.

¹¹This implies that the payoffs of both projects, when successful, are sufficient to repay all investors. A sufficient condition for this is: $H > V > F$, as, when everyone invests, the maximum repayment is F .

$V - I$, plus any internal funds available after paying external investors $K(\theta) - W(\theta)F$. With probability $1 - p$ the LR project fails, the firm cannot repay the investors in full, and its profit is zero.¹² Likewise, when the total funds are positive but not very high (i.e., $0 < K(\theta) < I$), the firm's expected profit from investing in the HR project is $q[H + K(\theta) - W(\theta)F]$, where q is the probability of success of the HR project, H is the return on the HR project, and $K(\theta) - W(\theta)F$ is the total amount of financing net of the amount owed to investors. With probability $1 - q$ the HR project fails, the firm cannot repay the investors in full, and its profit is zero. In Appendix A.1, we show that equation (3) implies that the firm's optimal investment strategy at date 1, conditional on the total available funding, is as follows:

$$\begin{cases} \text{Invest in LR project} & \text{if } K(\theta) \geq I \\ \text{Invest in HR project} & \text{if } 0 \leq K(\theta) < I \\ \text{Default} & \text{if } K(\theta) < 0. \end{cases} \quad (4)$$

Equation (4) indicates that the firm defaults when its external financing falls short of covering the ongoing operation losses ($K(\theta) < 0$), while the firm selects the LR project when its total funds available cover the fixed investment ($K(\theta) \geq I$). The firm, in turn, chooses the high-risk project whenever it lacks sufficient funds to invest in the low-risk project ($0 \leq K(\theta) < I$).

Information structure

Investors do not observe the true value of θ . However, before deciding whether to buy the bond, each investor j receives a private signal about θ : $x_j = \theta + \epsilon_j$, where the error terms ϵ_j are uniformly distributed over $[-\epsilon, \epsilon]$ and are independent across all investors. This information structure allows us to solve the game in the standard global games framework (Carlsson and Van Damme, 1993; Morris and Shin, 1998, 2004). All investors are identical and their actions are strategic complements (i.e., an investor's incentives to buy the bond increase with the number of other investors that also buy the bond).¹³ Furthermore, investors

¹²With probability $1 - p$ the LR project fails and there is no payoff for the firm since: $-I + K(\theta) - W(\theta)F < 0$. One can verify that this is equivalent to $(-I + \theta) + [W(\theta) - W(\theta)F] < 0$, which holds given that $I \geq \bar{\theta}$ and $F > B$ by assumption.

¹³In the context of our framework, the core challenge predominantly pertains to the inherent market structure. Notably, the coordination issue can be effectively mitigated under specific conditions. First, the presence of a singular funding entity, such as a bank, would avert this issue. Second, firms' credibly pledging

may observe a public credit rating provided by the CRA in addition to their private signals.

The Credit Rating Agency

The CRA observes perfectly the firm’s true fundamentals and its optimal investment strategy. Therefore, the forward-looking CRA assigns a rating R by taking into account its effects on the firm’s optimal investment strategy and its subsequent probability of default. Following [Boot *et al.* \(2006\)](#) and [Goldstein and Huang \(2020\)](#), we restrict the space of ratings to $R=\{0, q, p\}$ with $p, q > 0$. A rating of zero is equivalent to default, while q and p correspond to the firm’s investment in the HR and LR projects, respectively. In line with the “issuer-pays” business model, we assume that the CRA receives higher revenues when assigning better credit ratings. The CRA also faces reputational or legal costs when assigning ratings $R = p, q$, and the firm defaults. We assume that if a firm with rating $R > 0$ defaults at $t = 1$, the reputational costs for the CRA are very large, such that the CRA does not assign a rating to firms it foresees defaulting at $t = 1$. If a firm with rating $R > 0$ defaults at $t = 2$, the CRA incurs a cost, and this cost is greater for $R = p$ as compared to $R = q$.¹⁴

2.2 Theoretical predictions about investors and firms’ behaviour

This section derives theoretical predictions of the model without the CRA (benchmark) and with the CRA. The details of the thresholds and proofs can be found in [Appendix A](#).

We first derive the equilibrium of the model without a CRA. We solve the model backwards as follows. First, given its total funding $K(\theta)$, the firm chooses its optimal strategy described in (4). As in models of global games, investors’ strategies are monotonic in their private signals. As such, investors adopt a cutoff strategy, where they invest for signals above a threshold signal, $\tilde{x}$, and do not buy the bond when $x_j < \tilde{x}$.¹⁵ They use the Bayes rule to

the return of funds in instances where insufficient capital is raised for a low-risk project, resembling the models observed in investment targets within peer-to-peer lending platforms or private equity funds, can also resolve this predicament.

¹⁴See [Appendix A.2](#) for more details regarding the CRA’s revenues and costs.

¹⁵This equilibrium strategy rests on the existence of *lower* and *upper dominance* regions below and above which an investor has a dominant strategy to either not buy or buy the bond. The *lower dominance* region consists of values of fundamentals so low that even if all investors bought the bond, the firm would still not cover the losses from the ongoing project and would default. Hence, in the lower dominance region,

update their beliefs about the firm's fundamentals given their signals and maximize their expected payoffs given the firm's and other investors' optimal strategies.

Theoretical prediction 1 (Benchmark without a CRA). *In the benchmark model without a CRA, there is a unique equilibrium described by $(\tilde{\theta}_1, \tilde{\theta}_2, \tilde{x})$ such that: (i) The firm's investment strategy is*

$$\begin{cases} \text{Invest in LR project} & \text{if } \theta \geq \tilde{\theta}_2 \\ \text{Invest in HR project} & \text{if } \theta \in [\tilde{\theta}_1, \tilde{\theta}_2) \\ \text{Default} & \text{if } \theta < \tilde{\theta}_1, \end{cases}$$

where $\tilde{\theta}_2 > \tilde{\theta}_1$; (ii) Investor j buys the firm's bonds if and only if $x_j \geq \tilde{x}$, where $\tilde{x}$ is obtained from the indifference condition (of buying or not buying the bond) of the marginal investor who receives signal $\tilde{x}$. (See proof in Appendix A.1)

Intuitively, the cut-off value of θ below which default occurs ($\tilde{\theta}_1$) is the threshold value at which the firm is indifferent between defaulting and investing in the HR project, i.e., $K(\tilde{\theta}_1) = \tilde{\theta}_1 + W(\tilde{\theta}_1)B = 0$. Similarly, the cut-off value above which the firm undertakes the LR project ($\tilde{\theta}_2$) is obtained from the firm's indifference condition of choosing between the LR and HR projects $K(\tilde{\theta}_2) = \tilde{\theta}_2 + W(\tilde{\theta}_2)B = I$.

We then extend the benchmark model and allow for the presence of a credit rating agency. The CRA takes as given the firm's and investors' strategies, and maps the firm's fundamentals into a rating by maximizing its expected profits. We can show that when the ratio of revenues to cost is sufficiently high, the CRA's equilibrium strategy is to inflate the rating by assigning only two ratings: $R(\theta) = \{0, p\}$ as follows:¹⁶

an investor's dominant action is not to buy the bond. The *upper dominance* region corresponds to high fundamental values for which the firm can self-finance the LR project, even if nobody buys the bond. Therefore, an investor's dominant action is to buy the bond.

¹⁶Because our goal is to study the relationship between potentially inflated ratings, investor behaviour, and firm investment, we focus on the parametrization of the CRA's incentives under which it is optimal for the CRA to inflate ratings (see Lemma 1 in Appendix A.2). We do not consider cases in which the CRA either deflates ratings or accurately reveals the firm's credit quality.

$$R(\theta) = \begin{cases} p & \text{if } \theta \geq \theta_1^* \\ 0 & \text{if } \theta < \theta_1^*. \end{cases} \quad (5)$$

In equilibrium, the CRA chooses a threshold θ_1^* above which a θ -firm receives a rating $R(\theta) = p$, while below the threshold the rating is $R(\theta) = 0$. Thus, we can define *rating inflation* as follows:

Definition 1 [Inflated Credit Rating] A credit rating is inflated if, in equilibrium, a θ -firm receives a rating of p (i.e., implying it will undertake the LR project at date 1), while the firm undertakes the HR project and has a credit quality of q .

Notice that potentially inflated ratings are still informative about firm fundamentals and affect the optimal decision of investors. This is because a potentially inflated rating implies that, if $R = p$, all investors know that $\theta > \theta_1^*$ and, as a result, that the firm's fundamentals are not extremely low to the extent that would trigger an immediate default at date 1. The details are provided in Lemma 1 in Appendix A.2. The equilibrium of the model with a CRA is described in the following theoretical prediction.

Theoretical prediction 2 (Model with a CRA). *The model with a CRA has a unique equilibrium described by $(\theta_1^*, \theta_2^*, x^*)$ such that*

- (1) *The credit rating agency will assign ratings according to (5).*
- (2) (i) *If $R = 0$, no investor buys bonds, and the firm defaults at date 1. (ii) If $R = p$, investors buy the bonds if and only if their private signals x_j exceeds x^* , where x^* is obtained from the indifference condition of the marginal investor who is indifferent between buying and not buying the bond.*

Table 1: Experimental parametrization

Number of investors (n)	5
Initial endowment	100
Range of fundamentals (IF)	$[-400, 200]$
Price of bond (B)	100
Face value of bond (F)	200
Probability of success of LR project (p)	0.9
Probability of success of HR project (q)	0.2
Amount of financing to undertake LR (I)	300
Amount of financing to undertake HR (i)	0
Signal noise (ϵ)	30

(3) *The firm's investment strategy is*

$$\left\{ \begin{array}{ll} \text{Invest in LR project} & \text{if } \theta \geq \theta_2^* \\ \text{Invest in HR project} & \text{if } \theta \in [\theta_1^*, \theta_2^*) . \\ \text{Default} & \text{if } \theta < \theta_1^* \end{array} \right.$$

where $\theta_2^* > \theta_1^*$. (See proof in Appendix A.2)

Intuitively, in the model with a CRA, the cutoff thresholds for both the firm and investors differ from those in the benchmark model. This is because investors receive a public signal, in addition to their private signals, allowing them to update their posterior beliefs about θ . Specifically, observing a positive – though potentially inflated – rating $R = p$ truncates their posterior beliefs about θ from below θ_1^* . As a result, investors are assured that the firm's fundamentals are not excessively weak.

2.3 Parametrization and hypotheses

We adapt the theoretical model for a laboratory experiment and calibrate it to numerically solve for the equilibrium thresholds described in Section 2.2, which inform our experimental design. This subsection also illustrates the real effects of inflated credit ratings under our specific parametrization.

Table 1 reports the parametrization used in our experimental design. Based on these values, we numerically solve for the equilibrium thresholds in Section 2.2, assuming a finite number of investors, n . Consistent with prior laboratory studies of global games, we estimate a reduced form of the game with finite players using the binomial distribution (see, for example Heinemann *et al.*, 2004, 2009; Peia and Vranceanu, 2019; Bayona and Peia, 2022). Specifically, a risk-neutral player who receives a threshold signal x^* is indifferent between buying a bond or not, provided all other players buy the bond when their signal is above x^* .¹⁷ Accordingly, for a given fundamental θ , a player invests if their signal exceeds x^* (i.e., with probability $m(\theta) \equiv \Pr(x_j \geq x^*|\theta)$). Therefore, for a given θ , the expected number of investors who buy the bond, when each player invests with probability $m(\theta)$, is given by $E[W(\theta)] = m(\theta)n$. Section A.3 of the Appendix details the equations used to compute the theoretical thresholds underlying Theoretical predictions 1 and 2. Figure 1 illustrates these thresholds and highlights the regions of firm fundamentals where a potentially inflated credit rating may generate real effects.¹⁸ All remaining experimental parameters follow the assumptions outlined in Section 2.1.

We identify the real effects of a CRA’s rating by comparing firms’ investment decisions – which determine investors’ expected payoffs – across different levels of the fundamentals in the benchmark model and in the model with a CRA. Specifically, we define the real effects of credit ratings as follows:

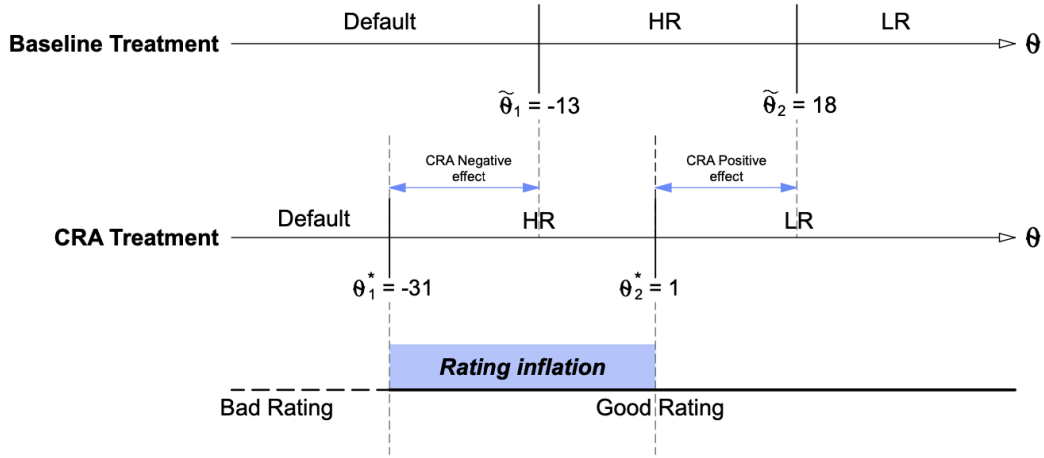
Definition 2 [Real Effects of Credit Ratings]: (i) A *positive real effect* occurs when a θ -firm invests in the LR project with a credit rating, but would have invested in the HR project without it. (ii) A *negative real effect* occurs when a firm that would have defaulted without the rating invests instead in the HR project.

Given the parametrization in Table 1 and as illustrated in Figure 1, we have $\theta_2^* > \tilde{\theta}_1$. Hence,

¹⁷This approach implicitly assumes that each investor is sufficiently small so that no single investor can influence the threshold signal. The experimental literature generally finds that $n = 5$ players is sufficient to ensure competitive outcomes (see, for example, Huck *et al.*, 2004).

¹⁸The equilibrium threshold signals above which buying the firm’s bonds is the dominant strategy are $\tilde{x} = 14$ in the benchmark model and $x^* = -5$ in the model with a CRA.

Figure 1: Equilibrium illustration of firm and CRA actions.



(potentially) inflated ratings have a negative real effect for $\theta_1^* \leq \theta < \tilde{\theta}_1$, as the firm invests in the HR project rather than defaulting. Conversely, they have a positive real effect for $\theta_2^* \leq \theta < \tilde{\theta}_2$, as the firm switches from investing in the HR project to the more efficient LR project. This result provides the basis for our hypotheses on the positive and negative effects of inflated ratings.

With this background, we can develop testable hypotheses on the effects of (potentially) inflated credit ratings on investors' actions and firms' project choices. Our first hypothesis concerns investor behaviour.

H1 (*Investing behaviour*). (i) *Higher signals about fundamentals increase the probability of investing.* (ii) *For intermediate values of fundamentals, a good (but potentially inflated) rating increases investors' propensity to buy the bond compared to when there is no CRA.*

Second, we conjecture that, when there is a CRA that inflates ratings, the higher level of external funds available to firms leads some of those with relatively low fundamentals to gamble for resurrection and invest in the high-risk project. As such, our second hypothesis is:

H2 (*Negative real effect of inflated ratings*). For similar levels of relatively low fundamentals, firms with a good (but potentially inflated) rating receive more external funds, leading to more investment in high-risk projects instead of defaulting, compared to when there is no CRA.

Given our specific parametrization, the threshold level of the firm's internal funds above which investing in the high-risk project is the firm's optimal strategy is lower in the equilibrium with a CRA than in the equilibrium without a CRA (i.e., $\theta_1^* < \tilde{\theta}_1$). We thus predict that for an intermediate range of relatively low firm fundamentals, there is more investment in the high-risk project when an inflated rating is available. Subsequently, early firm default is less likely in the presence of a public credit rating. This prediction follows from our comparison of investment thresholds between the benchmark model and the model with a CRA, where we have shown that a lower probability of firm default at date 1 is associated with the provision of ratings. Thus, unless a firm's fundamentals are very poor, we expect that a firm enjoys an increased supply of funds from investors when the rating is available. Better access to finance, in turn, increases the probability that external funds will cover potential losses from ongoing activities, reducing the likelihood of early default.

At the same time, the increased availability of external funding in the presence of potentially inflated ratings allows some firms with relatively high fundamentals to undertake low-risk projects. Our third hypothesis predicts that:

H3 (*Positive real effect of inflated ratings*). For similar levels of intermediate fundamentals, firms with a good (but potentially inflated) rating receive more external funds, leading to more investment in low-risk projects, instead of high-risk ones, compared to when there is no CRA.

Note that the threshold level of firm fundamentals above which investing in the low-risk project is the firm's optimal strategy is lower in the equilibrium with a CRA than when the CRA is absent (i.e., $\theta_2^* < \tilde{\theta}_2$). We predict that for an intermediate range of relatively high firm fundamentals, there is more investment in the low-risk project when an inflated rating

is available.

3 Experimental design and procedures

We design a laboratory experiment to understand the informational role of potentially inflated credit ratings and their impact on investment decisions. The experiment has two parts. In Part I, participants play the role of investors who decide whether to buy the bond issued by a firm or not. The computer plays the role of the firm and takes the optimal investment decisions as outlined in (4). Participants play the coordination game for 15 independent rounds in groups of five with random matching between rounds. Subjects are endowed with 100 experimental currency points (EC) in each round. They have to choose one of the following two decisions: (a) *Do not invest* and keep the initial 100 EC or (b) *Invest* and finance the firm with 100 EC.

If a participant chooses to invest, their payoff from investing depends on the firm's action. If the firm invests in the LR project, participants obtain 200 EC with 90% probability and 0 with 10% probability. When the firm invests in the HR project, participants get 200 EC with 20% probability and 0 with 80% probability. Finally, participants obtain 0 EC with certainty if the firm defaults.

The firm's action depends on how much financing is available. There are two types of funds: internal (IF), representing the firm's fundamentals, θ , and external (EF). In each round, the firm's IF are randomly selected from the uniform distribution $U \sim [-400, 200]$. This number is the same for all the investors in a group. The EF depend on how many investors from a group choose to invest. Similar to (4), the firm's decision is as follows: if $300 \leq IF + EF$, the firm has enough funds to take the LR project; otherwise, the firm chooses the HR project when $0 \leq IF + EF < 300$ or defaults when $IF + EF < 0$.

We consider two treatments in a between-subject design, which differ in the information provided to participants: the *Baseline treatment* and the *CRA treatment*. Participants receive a private signal about the firm's IF in both treatments. The signal is drawn independently

from the uniform distribution $U[IF - 30, IF + 30]$. In the Baseline treatment, participants do not receive further information beyond their noisy private signal. In contrast to the Baseline treatment, in the CRA treatment participants also observe a public credit rating about the firm’s ability to repay its creditors.

Specifically, we inform participants in the CRA treatment that there is a credit rating agency that assigns a public credit rating to the firm before participants’ decisions and the firm’s action. In the instructions, we explain that a credit rating is a grade that indicates the firm’s ability to repay its investors. The rating can be either A or B (corresponding to the potentially inflated rating, p , and the default rating, 0 , from Section 2, respectively). We inform participants that, in each round, the rating agency uses a theoretical scoring model to predict the ability of the firm to repay its investors. We explain how the CRA’s model considers the firm’s IF (which it knows perfectly), and how the rating might affect a hypothetical investor’s decision and, thus, the total amount of funds available to the firm and its corresponding action. Participants receive the following information regarding the process of assigning the ratings:

Rating of A when the firm’s IF are greater than or equal to -31 . The CRA estimates that the A-rated firm will invest in the LR project and investors have a 90% probability of being repaid.

Rating of B when the firm’s IF are smaller than -31 . The CRA estimates that the B-rated firm will default and investors have a 0% probability of being repaid.¹⁹

Participants are not explicitly informed that the rating may be inflated.

In each round, before taking their decisions, we elicited participants’ beliefs about the true level of the firm’s internal funds and the behaviour of other subjects in their group.²⁰ First, we asked participants to provide a point estimate for the firm’s IF. Then, all participants

¹⁹Note that -31 corresponds to the theoretical threshold θ_1^* from Theoretical prediction 2 under our parametrization from Table 1.

²⁰Beliefs have been shown to affect outcomes in coordination games similar to ours (Szkup and Trevino, 2020; Baeriswyl and Cornand, 2021).

had to state how many other subjects from their group were expected to invest.²¹ Once beliefs were elicited, participants had access to a simulator and could make their decision.

Participants received written instructions at the beginning of the session. In the instructions, we provide examples of the firm’s actions and investors’ expected payoffs conditional on hypothetical estimated values of the IF and a hypothetical number of participants who choose to invest.²² Before Part I of the experiment started, each participant had to pass a test with control questions to ensure that they understood the payoff structure and the decision process.²³ After all participants have made their decisions, they learn at the end of each round about the true level of the firm’s IF, how many other participants choose Invest, the firm’s action, and their potential payoffs in EC.

In Part II of the experiment, we asked participants to conduct two individual incentivized tasks to assess their risk and loss aversion, which have been shown to matter in coordination games similar to ours (Brown *et al.*, 2017; Kiss *et al.*, 2018). In the first task, we elicited risk aversion as in Eckel and Grossman (2008) and Dave *et al.* (2010). In the second task, participants answered a loss aversion questionnaire based on Gächter *et al.* (2022). Participants earned EC points depending on the outcome of the risky lotteries they chose in each task. After Part II of the experiment, we asked several questions regarding their behaviour throughout the experiment (using Likert scales) and elicited selected socioeconomic characteristics through an on-screen questionnaire. In terms of earnings, the computer randomly selected one of the 15 rounds from Part I to determine the participants’ payoffs for this part of the experiment. We informed participants about their earnings for Part I and Part II of the experiment at the end of the session. For both parts of the experiment, 15 EC translated into 1 Euro for payment.

We conducted 24 experimental sessions, each with 15 or 20 participants. In total, 445

²¹Online Appendix C presents screenshots from the first part of the experiment. Participants’ beliefs were not incentivized.

²²Online Appendix B provides the instructions for the CRA treatment.

²³The experiment was programmed and conducted using z-Tree software (Fischbacher, 2007). Online Appendix C presents the practice questions in Figure C.1. These questions were not incentivized.

students (225 in the Baseline treatment and 220 in the CRA treatment) participated at ESADE’s Decision Lab and Universitat Pompeu Fabra BESLab, both in Barcelona, Spain. Table C.1. in the Online Appendix summarizes the sessions. On average, participants earned 18 Euros, and the experiment lasted approximately 75 minutes.

4 Results

We present the results by first describing aggregate investment behaviour and firm outcomes at the group level, followed by an analysis of the predictors of individual investment behaviour. We then investigate the channels that explain differences in investment behaviour across treatments.

4.1 Group level analysis

We start by analyzing how investment behaviour changes across the two treatments for different values of fundamentals or firms’ internal funds (IF). Specifically, we compare the provision of external funding for firms with similar values of IF that correspond to the Good (A) or Bad (B) rating, but for which the rating is only observed in the CRA treatment. Table 2 provides summary statistics of the aggregate investment behaviour per treatment depending on whether fundamentals are sufficiently high (low) to receive a good (bad) rating. For both treatments, we report the average number of investors for firms with fundamentals below and above the threshold separating the two ratings in the CRA treatment.²⁴ These averages are based on group outcomes in our sample of 1,335 unique group-period observations (89 random groups $\times$ 15 periods).

We observe a higher average number of investors in the CRA treatment compared to the Baseline for values of the fundamentals corresponding to the Good rating (A) (column 1 vs. column 3) and a lower average number of investors for the Bad rating (B) (column 2 vs.

²⁴The threshold above which a Good rating (A) is assigned equals -31. Participants are informed about the value of this threshold in the CRA treatment instructions.

Table 2: Average number of participants investing in each treatment

Treatment	Baseline		CRA		Tests (p-values)			
	(1) Rating A	(2) Rating B	(3) Rating A	(4) Rating B	(1) vs. (3) Test 1	(3) Test 2	(2) vs. (4) Test 1	(4) Test 2
Hypothetical/ Observed rating								
Investors	3.96 (1.23)	0.78 (0.99)	4.29 (0.96)	0.38 (0.67)	0.00	0.02	0.00	0.00
Observations	303	372	297	363	600	24	735	24

Notes: Columns (1)-(4) present the mean (standard deviation) of the number of subjects (per group) investing, conditional on the treatment and observed (in the CRA treatment)/hypothetical (in the Baseline treatment) rating. Test 1 is a t-test of equality of means performed at the group level. Test 2 is the non-parametric Mann-Whitney U test performed at the session level.

column 4). Throughout the analysis, we assess the statistical significance of the differences across treatments through t-tests at the group level (1,335 group-period observations) and non-parametric tests (Mann-Whitney U test) at the session level (12 observations per treatment).²⁵ These tests, presented in the last four columns of Table 2, show that the observed differences are statistically significant across both tests.

Result 1 *Firms in the CRA treatment with a good (bad) rating receive significantly more (less) external funding than firms in the Baseline treatment with similar fundamentals.*

We further examine the relationship between firm fundamentals and group investment behaviour through regressions at the group (firm) level. Table 3 investigates whether the size of external funding (i.e., the number of investors buying bonds) varies across treatments for different levels of fundamentals. We estimate a series of Poisson models where the dependent variable is the number of investors buying the firm’s bond, and the main covariate is an indicator equal to one for the CRA treatment and zero for the Baseline treatment. All specifications control for the size of the firm’s internal funds (IF) and a period scalar.

Column (1) shows that external financing increases with internal funds, as expected. The CRA treatment dummy in column (1) is not statistically significant, indicating no average difference in investments across treatments. However, consistent with Table 2, we find het-

²⁵These results are also robust to correcting p-values for the multiplicity of hypotheses tested using the Bonferroni correction. Our two hypotheses refer to differences between treatments for values of the fundamentals above and below the ratings threshold. These additional results are available upon request.

Table 3: Size of investment across different ranges of fundamentals

	(1) Full sample	(2) Bad rating (B)	(3) Good rating (A)	(4) Quartile 1	(5) Quartile 2	(6) Quartile 3	(7) Quartile 4
IF	0.006*** (0.000)	0.007*** (0.001)	0.002*** (0.000)	0.003 (0.002)	0.012*** (0.001)	0.014*** (0.001)	0.001*** (0.000)
CRA treatment	-0.032 (0.041)	-0.714*** (0.152)	0.080** (0.031)	-0.638** (0.287)	-0.802*** (0.182)	0.097 (0.069)	0.028* (0.016)
Period	0.002 (0.004)	-0.057*** (0.010)	0.010*** (0.002)	-0.111*** (0.024)	-0.058*** (0.019)	0.008 (0.005)	0.006*** (0.002)
Observations	1,335	735	600	335	333	339	328

Notes: The table presents estimates from Poisson regressions where the dependent variable is the number of investors in a group buying the firm's bond. Column (2) is estimated for the subsample of fundamentals below -31, which corresponds to the Bad rating (B). Column (3) is estimated for the subsample of fundamentals above -31, which corresponds to the Good rating (A). Quartile 1 corresponds to $IF \in [-400, -222]$, Quartile 2 to $IF \in [-221, -62]$, Quartile 3 to $IF \in [-61, 19]$, while Quartile 4 to $IF \in [20, 200]$, respectively. *CRA treatment* is an indicator variable equal to 1 for the treatment with a credit rating. *Period* indicates the round of the investment game. Constant terms are included, but not reported. Standard errors, clustered at the session level, are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

erogeneity across ratings. For fundamentals corresponding to a Bad rating (B), the average number of investors is significantly lower in the CRA treatment relative to Baseline (column (2)). By contrast, for firms with fundamentals corresponding to a Good rating (A), external investment is significantly higher in the CRA treatment (column (3)).

Further analysis of the aggregate investment behaviour across quartiles of internal funds (columns (4)-(7)) reveals additional differences. For relatively low fundamentals (i.e., 1st and 2nd quartiles), investment is significantly lower in the CRA treatment compared to the Baseline. Conversely, for relatively high fundamentals (i.e., 3rd and 4th quartile), investment is higher under the CRA treatment, although these estimates are only mildly significant for the 4th quartile.²⁶

These findings suggest that ratings convey valuable information to market participants, consistent with evidence from natural experiments (Kliger and Sarig, 2000; Tang, 2009; Cornaggia *et al.*, 2018). We complement this literature by examining the informational channels through which rating inflation influences investor decisions and market outcomes.

The observed variations in external funding across treatments translate into significant dif-

²⁶Table 9 in Appendix B reports the average number of investors across quartiles of fundamentals together with non-parametric session-level tests. The results are consistent with the Poisson regressions in Table 3.

Table 4: Firms' automated actions across treatments

Treatment	Baseline			CRA			Non-parametric test (p-values)		
Firm action	(1) Default	(2) HR	(3) LR	(4) Default	(5) HR	(6) LR	(1) vs. (4)	(2) vs. (5)	(3) vs. (6)
Panel A: All fundamentals									
Proportion of firms	0.44 (0.06)	0.22 (0.04)	0.36 (0.05)	0.48 (0.05)	0.17 (0.08)	0.40 (0.06)	0.10	0.02	0.15
Observations	292	141	242	311	90	259	24	24	24
Panel B: Fundamentals corresponding to a Bad rating (B)									
Proportion of firms	0.78 (0.08)	0.23 (0.06)	0.04 (0.02)	0.86 (0.06)	0.17 (0.07)	-	0.03	0.03	-
Observations	288	79	5	311	52	0	24	24	-
Panel C: Fundamentals corresponding to a Good rating (A)									
Proportion of firms	0.06 (0.03)	0.24 (0.08)	0.79 (0.09)	-	0.26 (0.16)	0.89 (0.12)	-	0.03	0.01
Observations	4	62	237	0	38	259	-	23	24

Notes: The table reports the proportion (standard deviation) of firms undertaking each action across the two treatments. Standard deviations are calculated at the session level. The non-parametric test is a Mann-Whitney U test at the session level, comparing the proportion of firms choosing specific actions across treatments. Panel A presents statistics for the full sample of 1,335 firms; Panel B restricts the sample to firms with fundamentals corresponding to a Bad rating (B); and Panel C to firms with a Good rating (A).

ferences in firms' automated actions, as shown in Table 4. Panel A reports the proportion of firms undertaking each of the three actions by treatment. We observe that, in the CRA treatment, a higher proportion of firms default, but there is also less investment in the HR project and more investment in the LR project. However, in non-parametric tests at the session level (reported in the last three columns of Table 4), only the difference in high-risk projects between the two treatments is statistically significant at conventional levels when we average across all levels of firm fundamentals and group-level decisions.

Panels B and C further explore these differences by separating firms with fundamentals corresponding to a Bad rating (B) and a Good rating (A), respectively. For bad ratings, firms in the CRA treatment default significantly more often (86% vs 78%), but also undertake significantly fewer high-risk projects (17% vs 23%). Notably, no firm receiving a Bad rating (B) undertakes the low-risk project in the CRA treatment, whereas in the Baseline, a small fraction of firms with fundamentals corresponding to a Bad rating (B) receive sufficient funding to do so. For Good ratings (A), firms in the CRA treatment invest significantly

more in low-risk projects (89% vs 79%), but also more frequently in high-risk projects (26% vs 24%). These differences are all statistically significant in session-level non-parametric tests.

Taken together, the results in Table 4 provide empirical support for Hypotheses H2 and H3: (potentially) biased good ratings increase investor participation, enabling more investment in low-risk projects (*positive real effect*) but also allowing more firms to undertake high-risk projects rather than default (*negative real effect*). We also document a strong impact of observing a Bad rating (B) in reducing high-risk investment. In the Baseline treatment, the absence of the public rating leads to higher investment in firms with weak fundamentals, resulting in more firms receiving sufficient funds to pursue high-risk projects. By contrast, observing a Bad rating (B) discourages investment, leading to more defaults rather than high-risk projects in the CRA treatment. Accordingly, the overall decline in high-risk projects observed in Panel A is driven by reduced funding for poorly rated firms in the CRA treatment.

This latter effect, while not captured in Goldstein and Huang (2020) or in our theoretical framework, is consistent with models in which ratings serve as focal points that coordinate behaviour around both good and bad ratings (such as Boot *et al.*, 2006). By contrast, the absence of a focal point in the Baseline treatment leads to excessive investment in defaulting firms.

Result 2: *As a result of investors’ financing decisions, (i) firms with a (potentially inflated) Good rating (A) invest more in both low-risk and high-risk projects in the CRA treatment than firms with similar fundamentals in the Baseline treatment, and (ii) firms with a Bad rating (B) undertake fewer high-risk projects and default more in the CRA treatment than firms with similar fundamentals in the Baseline treatment.*

These findings are confirmed in Table 5, which reports multinomial logit regressions of firms’ actions conditional on the presence of a credit rating in the CRA treatment. The dependent variable is categorical (Default, HR, LR), and we examine how the likelihood of each action changes for rated firms in the CRA treatment relative to firms with similar fundamentals

Table 5: Ratings and firms' actions

	Bad rating (B)		Good rating (A)	
	(1)	(2)	(3)	(4)
<i>Baseline outcome: High risk</i>	Default	Low risk	Default	Low risk
Internal funds (IF)	-0.038*** (0.003)	0.024* (0.013)	-0.098 (0.062)	0.070*** (0.008)
CRA treatment	1.123*** (0.363)	-14.597*** (0.570)	-14.343*** (0.727)	1.003** (0.484)
Observations	735	735	600	600

Notes: The table reports estimates from multinomial logit regressions where the dependent variable is the firm's action: default, high-risk project, or low-risk project. Columns (1)-(2) present results for values of fundamentals corresponding to a Bad rating (B) (i.e., below -31), and columns (3)-(4) for a Good rating (A) (i.e., above -31). The baseline category is the high-risk project. Columns (1) and (3) report the log-odds coefficients of Default relative to the high-risk project, while columns (2) and (4) report those of choosing the low-risk project relative to the high-risk one. *Internal funds (IF)* captures the firm fundamentals. *CRA treatment* is an indicator variable equal to 1 for the treatment with a credit rating. Constant terms and period scalars are included, but not reported. Standard errors, clustered at the session level, are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

in the Baseline. We estimate separate regressions for fundamentals corresponding to a Bad rating (B) (columns (1)-(2)) and a Good rating (A) (columns (3)-(4)). The main independent variable is a CRA treatment dummy, with controls for internal funds (IF) and a period scalar. The high-risk project serves as the baseline outcome, so Table 5 reports the log odds of default or low-risk investment relative to high-risk investment.

The results are as follows. For fundamentals associated with a Bad rating (B), receiving a public rating in the CRA treatment significantly increases the likelihood (log odds) of default relative to high-risk investment (column (1)), while also reducing the likelihood of low-risk investment compared with firms with similar fundamentals in the Baseline (column (2)). Conversely, for fundamentals corresponding to a Good rating (A), receiving a credit rating significantly increases the likelihood of low-risk investment relative to high-risk investment (column (4)). In addition, column (3) shows that default is less likely for firms with fundamentals corresponding to a Good rating (A) in the CRA treatment.²⁷

²⁷While the magnitudes of the effects are of secondary importance in an experimental setting, Appendix Table 10 reports the marginal effects corresponding to the log-odds ratios in Table 5. The results suggest shifts of roughly 10 percentage points in the probability of default or low-risk investment relative to high-risk investment across different fundamentals.

Overall, these results suggest that public ratings in the CRA treatment reduce investment in high-risk projects through two channels: (i) bad ratings decrease external funding, leading to higher default, while (ii) good ratings increase external funding, allowing more firms to shift from high-risk to low-risk projects. At the same time, we also observe more high-risk investments relative to default under (potentially) inflated ratings, consistent with some firms obtaining sufficient funding to “gamble for resurrection”.

Result 3 *As a result of aggregate investors’ decisions: (i) Receiving a Good rating (A) in the CRA treatment increases the likelihood that firms invest in low-risk projects rather than high-risk ones, relative to firms with similar fundamentals in the Baseline treatment. It also enables more firms to undertake high-risk projects instead of defaulting. (ii) Conversely, firms with a Bad rating (B) in the CRA treatment are more likely to default than to undertake high-risk projects, relative to firms with similar fundamentals in the Baseline treatment.*

We next examine individual decisions and the potential channels that may explain differences in investment behaviour across treatments.

4.2 Individual investment behaviour

We begin by examining whether subjects’ investment decisions increase with the private signal (hint) about the firm’s internal funds, as predicted by the global games methodology.

Table 6 reports a multivariate analysis of individual investment probabilities across subsamples defined by different levels of fundamentals. Across all samples, investment is positively and statistically significantly related to the hint about IF, consistent with Hypothesis H1. Consistent with the group-level results in Table 3, we find no significant differences in the average probability of investing across treatments (column (1)). However, in the CRA treatment, individuals who receive a Bad rating (B) invest significantly less than those who receive a similar signal about fundamentals, but no rating, in the Baseline treatment (column (2)). The opposite pattern emerges for a Good rating (A) in column (3), where the coefficient is positive and strongly significant. These differences persist when we split funda-

Table 6: Probability of investing across different ranges of fundamentals

	(1) All	(2) Bad rating (B)	(3) Good rating (A)	(4) Quartile 1	(5) Quartile 2	(6) Quartile 3	(7) Quartile 4
Hint about IF	0.010*** (0.001)	0.006*** (0.001)	0.013*** (0.001)	0.003** (0.002)	0.011*** (0.001)	0.027*** (0.002)	0.008*** (0.002)
CRA treatment	-0.097 (0.077)	-0.615*** (0.133)	0.406*** (0.118)	-0.552* (0.291)	-0.750*** (0.163)	0.210* (0.124)	0.233 (0.176)
Period	-0.003 (0.006)	-0.047*** (0.010)	0.051*** (0.010)	-0.116*** (0.026)	-0.052*** (0.016)	0.027*** (0.010)	0.066*** (0.017)
Observations	6,675	3,675	3,000	1,675	1,665	1,695	1,640

Notes: The table presents estimates from probit regressions for different samples, where the dependent variable is an indicator equal to 1 if the investor buys the firm's bond. Column (2) corresponds to the subsample of fundamentals below -31 (Bad rating, B), and Column (3) to fundamentals above -31 (Good rating, A). Quartile 1 corresponds to $IF \in [-400, -222]$; Quartile 2 to $IF \in [-221, -62]$; Quartile 3 to $IF \in [-61, 19]$; and Quartile 4 to $IF \in [20, 200]$. *Hint about IF* captures the private information about firm fundamentals. *CRA treatment* is an indicator variable equal to 1 if the treatment is CRA. *Period* indicates the round of the investment game. Constant terms are included, but not reported. Standard errors, clustered at the individual level, are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

mentals into quartiles (columns (4)-(7)). The probability of investing is significantly lower in the CRA treatment for the 1st and 2nd quartiles of fundamentals, and higher for the 3rd and 4th quartiles, although the latter effects are only marginally significant in the 3rd quartile and not significant in the 4th quartile.²⁸

We next examine whether participants' actions are consistent with their elicited beliefs. Table 7 reports regressions of individual investment probabilities on participants' stated beliefs about the true value of the fundamentals and the number of others investing, both elicited prior to each decision. Columns (1) and (4) show that investment increases with beliefs about fundamentals: the coefficient of *Belief about IF* is positive and statistically significant. Columns (2) and (5) reveal a similar positive relationship between the likelihood of investing and beliefs about others' actions. To make the magnitudes of the point estimates comparable, we standardize both belief measures (i.e., *Belief about IF* and *Belief about # investors*). Across all specifications, the estimated coefficients of *Belief about # investors* exceed those of *Belief about IF*, indicating that expectations about others' behaviour exert a stronger influence on investment decisions than beliefs about fundamentals. Columns (3) and (6), which include both beliefs simultaneously, confirm that the expected behaviour of

²⁸The results in Table 6 are robust to splitting the sample by quartiles of the hints received rather than fundamentals.

Table 7: Probability of investing across treatments

	Baseline			CRA		
	(1)	(2)	(3)	(4)	(5)	(6)
Belief about IF	1.472*** (0.104)		0.623*** (0.093)	1.967*** (0.167)		0.805*** (0.113)
Belief about # investors		2.172*** (0.114)	1.919*** (0.120)		2.140*** (0.122)	1.778*** (0.121)
Period	-0.000 (0.009)	-0.015 (0.010)	-0.010 (0.010)	0.030*** (0.008)	0.007 (0.011)	0.025** (0.011)
Observations	3,375	3,375	3,375	3,300	3,300	3,300

Notes: The table presents estimates from probit regressions where the dependent variable is an indicator equal to 1 if the investor buys the firm's bond. *Belief about IF* and *Belief about # investors* capture the stated beliefs (as a number) regarding the firm's fundamentals and the number of other participants investing, respectively. Both variables are standardized in the regressions. Standard errors, clustered at the subject level, are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

others is the stronger predictor of investment.²⁹

Result 4: *Beliefs about other investors' behaviour are a strong predictor of a participant's investment decision, whereas beliefs about the firm's fundamentals exert a weaker influence.*

4.3 Channels

We consider two channels that may explain the differences in behaviour across treatments. The first channel relates to the effect of ratings on beliefs about firm fundamentals. In the theoretical model presented in Section 2, inflated ratings have real effects because they provide useful information to investors: a good rating rules out very weak fundamentals, and thus implies that the firm will not default early. Consequently, we conjecture that potentially inflated ratings may increase the propensity to invest by conveying positive information about the firm. Specifically, due to the partial verifiability constraint imposed on the CRA, observing a Good rating (A) truncates investors' posterior beliefs about the firms' fundamentals. This, in turn, can make investors more optimistic about the firm's prospects and more willing to buy its bond.

We begin by investigating how credit ratings affect investors' posterior beliefs about firm

²⁹The regressions in Table 7 exclude the hint about fundamentals, which is highly correlated with stated beliefs about IF (correlation coefficient is 0.93).

fundamentals. In particular, for regions of IF that are close to the rating threshold, observing the rating should allow subjects to form more accurate posterior beliefs about the firm’s IF.³⁰ Panel (a) of Figure 2 shows the average stated belief about IF alongside the average theoretical belief defined as the expected value of the Bayesian posterior distribution of the fundamental given the realized signals.³¹ We find that average posterior beliefs about fundamentals near the rating threshold do not differ significantly across treatments (p-value=0.13; 0.91).³² However, participants appear more optimistic in the CRA treatment for Good ratings (A): average beliefs about fundamentals (IF) are higher in the CRA treatment as compared to the Baseline (p-value<0.01; 0.04). For Bad ratings (B), beliefs are more pessimistic, i.e., on average lower in the CRA treatment (p-value=0.06; 0.08).

Panels (b) and (c) of Figure 2 show forecast errors in forming beliefs, which we measure as the difference between stated beliefs and actual fundamentals. Panel (b) plots positive forecast errors (beliefs above realized IF), while Panel (c) plots negative forecast errors (beliefs below realized IF). Participants in the CRA treatment exhibit larger positive forecast errors following a good rating (p-value<0.01; 0.07). Even when forecast errors are negative, beliefs in the CRA treatment remain higher – implying smaller negative errors – after a good rating (p-value<0.01; <0.01). Taken together, these results suggest that good ratings systematically bias participants toward overoptimism about fundamentals, whereas bad ratings do not significantly affect belief formation.

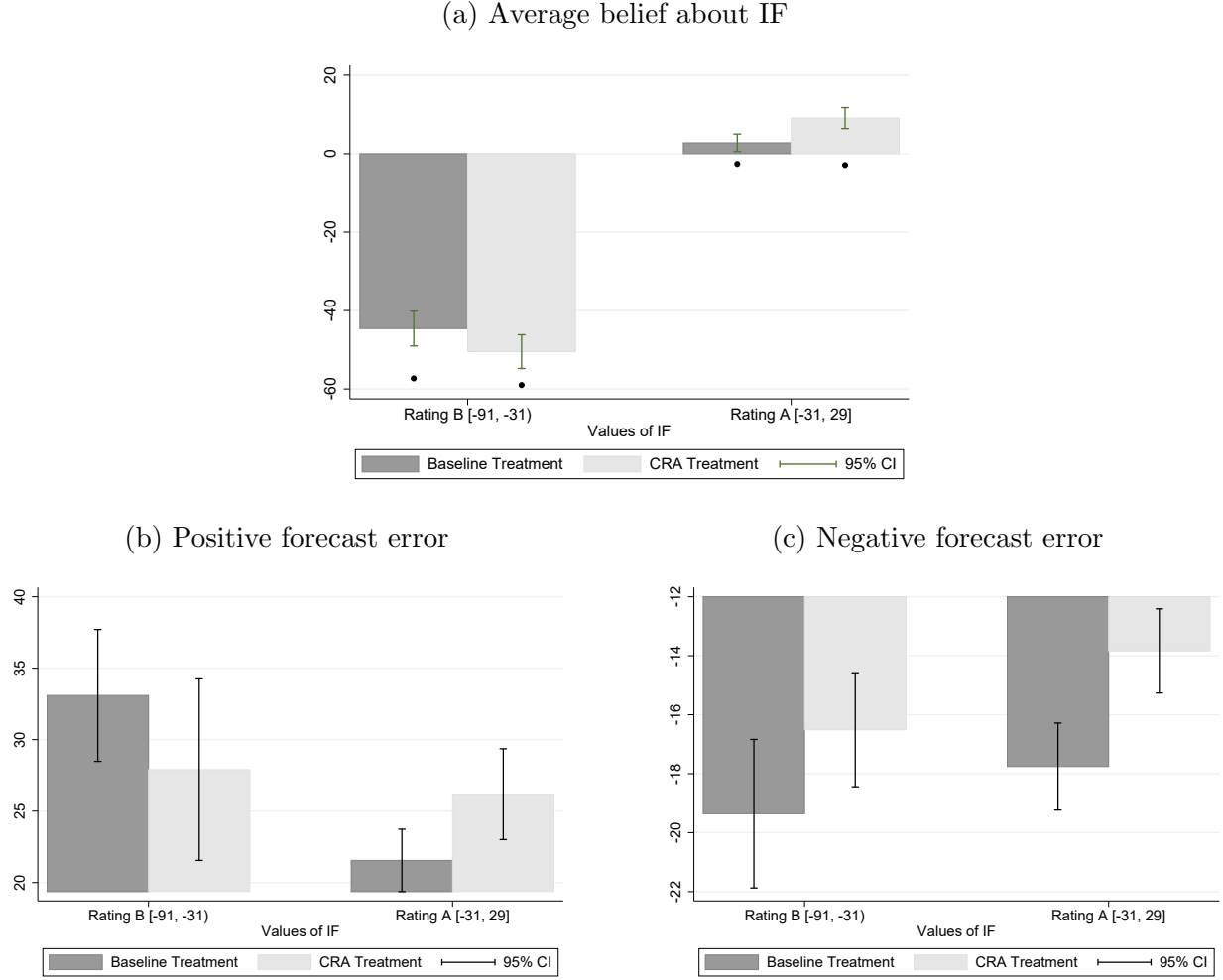
Result 5: *Posterior beliefs about the firm’s fundamentals are not statistically different between treatments near the rating threshold. However, relative to the Baseline treatment, investors in the CRA treatment are more optimistic about fundamentals following a Good*

³⁰Specifically, for fundamentals within 2ϵ of the theoretical threshold, observing the rating yields a truncated posterior distribution. This is because for a given $\theta = \theta_1^*$ subjects observing the lowest ($\theta_1^* - \epsilon$) or highest ($\theta_1^* + \epsilon$) private signal will have a posterior distribution of θ over the maximum interval $[\theta_1^* - 2\epsilon, \theta_1^* + 2\epsilon]$.

³¹For the range of fundamentals considered, in the Baseline treatment the Bayesian posterior belief about IF upon observing a signal x_i is: $E[IF|x_i] = x_i$. In the CRA treatment, the expectation is truncated around the rating threshold of -31. Specifically, for a Good rating (A): $E[IF|x_i] = [\max(-31, x_i - 30) + (x_i + 30)]/2$; for a Bad rating (B): $E[IF|x_i] = [(x_i - 30) + \min(-31, x_i + 30)]/2$.

³²Throughout this section, p-values reported in parentheses correspond to (1) a t-test on the full sample of individual decisions and (2) a non-parametric Mann-Whitney test performed at the session level.

Figure 2: Beliefs about the firm's fundamentals



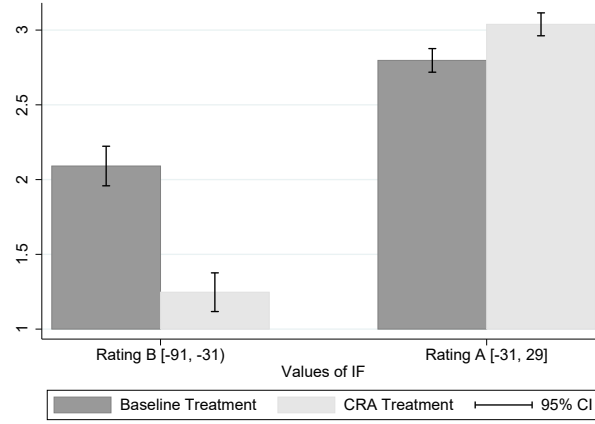
Notes: Panel (a) shows the average stated belief across participants about the value of the firm's fundamentals around the rating threshold (-31). The dots in Panel (a) represent the average theoretical beliefs derived from Bayesian updating based on the realized signals received by participants. Panels (b) and (c) show the average forecast error, defined as the difference between stated beliefs and actual fundamentals. Panel (b) reports positive forecast errors (stated beliefs above actual fundamentals), while Panel (c) reports negative forecast errors (stated beliefs below actual fundamentals). Whiskers mark the 95% confidence interval.

rating (A) and more pessimistic following a Bad rating (B). Moreover, Good ratings (A) systematically bias participants' beliefs towards overoptimism about a firm's fundamentals.

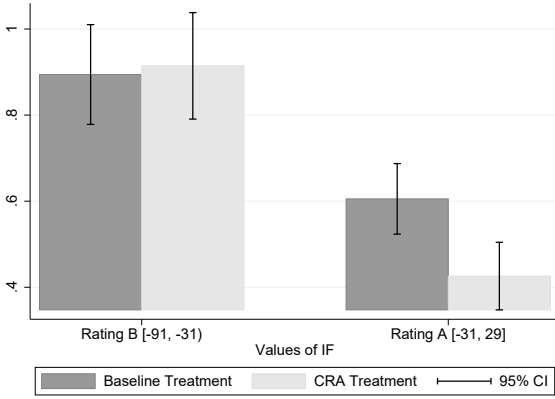
A second channel that may explain the differences in investors' behaviour across treatments concerns how ratings shape beliefs about the behaviour of others. Public credit ratings may not always convey new information about fundamentals, but can instead serve as a

Figure 3: Beliefs about the investment behaviour of others

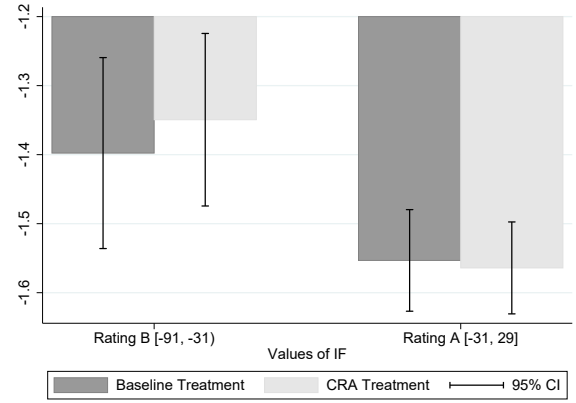
(a) Average belief about the number of investors



(b) Positive forecast error



(c) Negative forecast error



Notes: Panel (a) shows the average stated belief across participants about the number of others investing around the rating threshold (-31). Panels (b) and (c) show the average forecast error, defined as the difference between stated beliefs and the actual number of other participants investing. Panel (b) reports positive forecast errors (stated beliefs above the actual number), while Panel (c) reports negative forecast errors (stated beliefs below the actual number). Whiskers mark the 95% confidence interval.

coordination device by revealing information about other investors' signals. Figure 3 reports average stated beliefs about the number of others investing around the rating threshold (Panel (a)) and the associated forecast errors (Panels (b) and (c)) across treatments. A forecast error measures the difference between the stated belief about how many others will invest and the actual number who invest. A positive (negative) forecast error implies overestimation (underestimation) of the actual number. In the CRA treatment, participants

expect significantly more investors to buy the bond when fundamentals correspond to a good rating (p-value < 0.001; 0.06) and significantly fewer when fundamentals correspond to a bad rating (p-value < 0.001; < 0.001) relative to the Baseline. However, ratings do not improve the accuracy of posterior beliefs: positive and negative forecast errors do not differ significantly between Baseline and CRA treatments around the rating thresholds.³³

Result 6: *Posterior beliefs about others' investment behaviour differ significantly across treatments near the rating threshold. Relative to the Baseline, investors in the CRA treatment are more optimistic about the investing behaviour of others following a Good rating (A) and more pessimistic following a Bad rating (B).*

We confirm these individual-level findings through a series of regressions that cluster standard errors at the subject level to account for the correlation in investment decisions across periods. Columns (1)-(2) of Table 8 report probit estimates of the probability of investing across treatments. The dependent variable is an indicator equal to 1 if a participant invests. Column (1) presents the treatment effect for fundamentals corresponding to a Good rating (A), and column (2) for a Bad rating (B). Consistent with our group-level results reported in Table 6, investors are more (less) likely to invest in firms receiving a Good (A) (Bad (B)) rating in the CRA treatment relative to firms with similar fundamentals in the Baseline treatment.

Columns (3)-(6) examine how ratings affect beliefs and confirm the results reported in Figures 2 and 3. Column (3) shows that observing a Bad rating (B) does not differentially affect the posterior beliefs about firm fundamentals across treatments, while beliefs are significantly higher when a Good rating (A) is observed (column (4)). Columns (5)-(6) report that beliefs about the number of others investing are significantly higher (lower) in the CRA treatment relative to the Baseline when fundamentals correspond to a Good (A) (Bad (B)) rating. Notably, the coefficient for the *CRA treatment* in column (6) is about half the absolute value of the coefficient in column (5), suggesting that the effect on beliefs is larger for the

³³In Panel (b) of Figure 3, participants appear to have a lower positive forecast error when receiving a Good rating (A), but this is significant only when comparing averages across individuals, not in non-parametric tests at the session level (p-value = 0.01; 0.14).

Bad rating (B).

Column (7) formally tests this asymmetry using an ordered logit model. The specification includes an interaction between the *CRA treatment* dummy and a *Rating dummy*, where the latter equals one for firms with fundamentals above the theoretical threshold in both treatments and zero otherwise. The dependent variable is the expected number of investors buying the bonds, and the estimation uses the full sample of individual decisions. The interaction term is positive and statistically significant, indicating that the difference in the slopes between the CRA and Baseline treatments for Good (A) versus Bad (B) ratings is statistically significant. A one-sided Wald test confirms that the treatment effect is larger in magnitude for fundamentals corresponding to a Bad rating (B). Specifically, the treatment effect for the Bad rating (B) (-1.094 in column (7)) is significantly larger in absolute value than that for the Good rating (A) ($-1.094 + 1.524 = 0.43$). The null hypothesis is rejected at conventional levels ($p < 0.01$), confirming that the effect of observing a rating in the CRA treatment on beliefs about others' investment behaviour is statistically larger for Bad rating (B) than for Good rating (A).

Result 7: *A Bad rating (B) has a larger effect on beliefs about the behaviour of other investors than a Good rating (A).*

Results 4-7 relate to models that study public and private signals in games with strategic complementarities (Heinemann *et al.*, 2004; Cornand and Heinemann, 2014b; Baeriswyl and Cornand, 2016; Shurchkov, 2016; My *et al.*, 2021). We provide novel empirical evidence on the mechanisms emphasized in this literature. A key result is that public information has a larger impact on equilibrium outcomes because public signals are more informative about the behaviour of others. Consistent with this view, we find that even potentially inflated public credit ratings act as focal points in participants' coordination problem. Both good and bad ratings have a strong coordination effect on investors' beliefs about their mutual investment behaviour, but only good ratings affect beliefs about fundamentals.

Notably, the enhanced coordination has overall positive implications in a setting with feed-

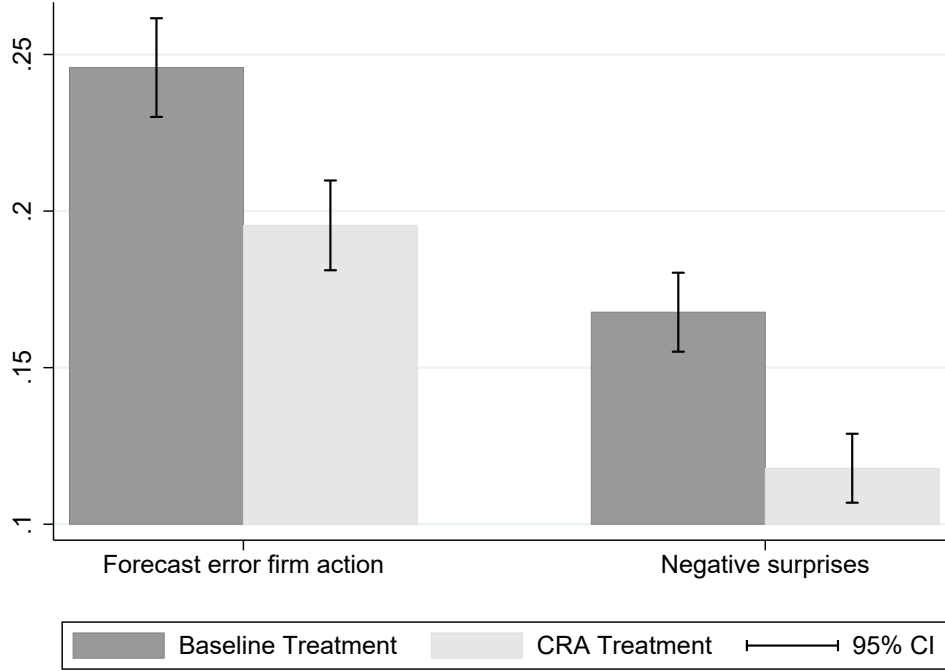
Table 8: Ratings, investment behaviour and beliefs

Dependent variable	(1)	(2)	(3)		(4)		(5)		(6)	(7)
	$\mathbb{1}\{\text{Invest} = 1\}$		Belief fundamentals		Belief number investors					
	Bad rating (B)	Good rating (A)	Bad rating (B)	Good rating (A)	Bad rating (B)	Good rating (A)	Bad rating (B)	Good rating (A)	Full sample	
Hint about IF	0.006*** (0.001)	0.013*** (0.001)	0.930*** (0.012)	0.872*** (0.011)	0.011*** (0.001)	0.015*** (0.001)				
CRA treatment	-0.615*** (0.133)	0.406*** (0.118)	2.291 (4.576)	3.938*** (1.517)	-1.065*** (0.121)	0.468*** (0.121)			-1.094*** (0.124)	
Period	-0.047*** (0.010)	0.051*** (0.010)	-2.308*** (0.340)	0.157 (0.126)	-0.071*** (0.009)	0.077*** (0.009)				
Rating dummy										0.743*** (0.111)
Rating dummy X CRA Treatment										1.524*** (0.167)
Observations	3,675	3,000	3,675	3,000	3,675	3,000				6,675
Number of subjects	445	445	445	445	445	445				445

Notes: Columns (1)-(2) report estimates from probit regressions where the dependent variable is an indicator equal to 1 if a participant invests. Columns (3)-(4) present estimates from OLS regressions where the dependent variable is the stated belief about the value of the firm's internal funds (IF). Columns (5)-(6) report estimates from ordered logit regressions where the dependent variable is the stated belief about the number of participants who buy the bond. Columns (1), (3), and (5) present regressions for a subsample of fundamentals below -31, corresponding to a Bad rating (B). Columns (2), (4), and (6) present regressions for a subsample of fundamentals above -31, corresponding to a Good rating (A). Column (7) uses the full sample of individual decisions. *Hint about IF* captures the private information about firm fundamentals. *CRA treatment* is an indicator variable equal to 1 if the treatment is CRA. *Period* indicates the round of the investment game. *Rating dummy* is an indicator variable equal to 1 for firms (in both treatments) with fundamentals above -31 and zero otherwise. Standard errors, clustered at the subject level, are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

back effects between the financial and real sectors. As shown in Section 4.1 (see Table 4), potentially inflated ratings lead, on average, to a significantly higher share of firms undertaking both the efficient low-risk project and the high-risk project. The mechanism is as follows: after good (potentially inflated) ratings, investors hold significantly higher beliefs about the number of others investing and display overoptimism about fundamentals. This leads to higher coordination on investing and, in a framework with feedback effects, results in more efficient firm investment and improved credit quality for some firms. At the same time, it enables firms with weak fundamentals to gamble for resurrection by pursuing high-risk projects. By contrast, a bad rating induces investors to coordinate on not investing, driven partly by lower expectations about fundamentals, but especially by the belief that others will not invest. This reduces external funding for firms with weak fundamentals and curtails their risky investment, an outcome we interpret as beneficial. Taken together, when ratings may be inflated, both good and bad ratings enhance coordination in ways that amplify positive real outcomes, underscoring the powerful role of public signals in shaping individual investment decisions and firm outcomes.

Figure 4: Expectations and realized firm action



Notes: The left panel shows the average forecast error about the firm action, measured as the absolute value of the difference between the expected and realized firm actions. The expected firm action is computed based on the stated beliefs about firm fundamentals and the behaviour of others. Firm actions are coded as 1, 2, and 3 corresponding to Default, HR, and LR, respectively. The right panel shows the percentage of negative surprises, defined as instances in which the firm's outcome is worse than expected. Whiskers mark the 95% confidence interval.

Finally, we examine whether participants are better able to forecast firms' actions and are less likely to be negatively surprised by outcomes in the CRA treatment. Figure 4 (left panel) reports the average forecast error about the firm's actions, defined as the absolute value of the difference between the expected and realized firm actions. Expected firm actions are derived from each subject's stated beliefs about firm fundamentals and the behaviour of others.³⁴ We find that participants can better forecast the actual firm action in the CRA than in the Baseline treatment (a t-test of differences in average individual forecast error yields a p-value < 0.001).

³⁴For example, if a participant who invests reports a belief of 50 for fundamentals and expects 3 others to invest, the expected firm action is LR, since $50 + 4 \times 100 > 300$.

This improved forecasting also reduces the incidence of negative surprises. We define a negative surprise as occurring when (i) the firm undertakes the HR project or defaults while the participant expected the firm to undertake the LR project, or (ii) the firm defaults while the participant expected an HR/LR project to be undertaken. Figure 4 (right panel) shows that the share of cases in which outcomes are worse than expected is significantly lower in the CRA treatment ($p\text{-value} < 0.001$).³⁵

Result 8: *Compared to the Baseline treatment, investors forecast firms' actions more accurately and experience fewer negative surprises in the CRA treatment.*

We provide additional results and robustness tests for our main findings in the Online Appendix. Specifically, we show that all our results remain robust when controlling for individual characteristics and for measures of risk and loss aversion. We also present additional results from a robustness treatment in which the possibility of inflated ratings is made more salient. This design allows us to distinguish whether the behavioural differences between the CRA and Baseline treatments arise from the mere presence of ratings, or from their potential inflation. Finally, we provide descriptive statistics from the post-experimental questionnaire, which corroborate our main results, particularly the central role of expectations about others' behaviour in the game.

5 Concluding remarks

We conduct a laboratory experiment to study the relationship between credit ratings, investor behaviour, and firm investment. Our study provides new empirical evidence on the potential mechanisms through which ratings can influence economic efficiency. Credit ratings can have significant economic consequences because they not only reflect but also affect

³⁵Using this negative-surprise measure, we can assess how often participants fail to best respond to their stated beliefs. We find that out of 6,675 decisions, only 275 (4.1%) involve participants investing despite expecting the firm to default or invest in high-risk projects, and only 94 (1.4%) involve not investing despite expecting a low-risk project. Thus, in the vast majority of cases, participants' actions are consistent with their stated expectations.

a debt issuer’s credit quality. Yet the impact of inflated credit ratings remains uncertain. On the one hand, inflated ratings may facilitate firms’ excessive risk-taking, resulting in adverse economic outcomes. On the other hand, they may enhance economic efficiency by providing informative – albeit potentially biased – signals that shape a firm’s financing costs and investment choices, thereby validating the original rating *ex post*. The net effect of inflated ratings remains therefore an empirical question, but one that has been difficult to address because inflated ratings are hard to identify and because unobserved confounding factors may jointly affect ratings and investors’ behaviour.

Our experimental design overcomes these challenges by controlling for firms’ fundamentals and investors’ information sets, thereby isolating the informational role of potentially inflated credit ratings. Our main findings suggest that both positive and negative effects of inflated credit ratings are present in the data, with the positive effects more likely to dominate. Inflated ratings serve as a coordination mechanism: they provide informative signals that shape investors’ beliefs about the investment behaviour of other investors while exerting only a modest influence on their beliefs about firm’s fundamentals. A good (potentially inflated) rating increases optimism about others’ behaviour, facilitating external funding and enabling firms to undertake value-enhancing projects. Conversely, a bad rating induces pessimism about others’ behaviour, reducing their incentive to provide funding and limiting excessive risk-taking by financially constrained firms. Our findings suggest that the potential adverse real effects of inflated credit ratings appear weaker, suggesting that such ratings may have positive effects beyond the laboratory in terms of efficient capital allocation and improved market outcomes.

Our findings imply that, from a policy standpoint, the interdependence between credit ratings and the actions of investors and firms is paramount. Inflated ratings can lead to greater economic efficiency if this feedback loop is present. In markets with credit rating agencies, even potentially inflated ratings provide valuable information that enhances resource allocation relative to markets without public ratings. An open question for future research is whether accurate credit ratings – those that most closely reflect a firm’s true credit risk –

improve economic efficiency beyond what inflated ratings achieve.

References

- ALLEN, F., MORRIS, S. and SHIN, H. S. (2006). Beauty contests and iterated expectations in asset markets. *Review of Financial Studies*, **19** (3), 719–752.
- ALMEIDA, H., CUNHA, I., FERREIRA, M. A. and RESTREPO, F. (2017). The real effects of credit ratings: The sovereign ceiling channel. *Journal of Finance*, **72** (1), 249–290.
- ALP, A. (2013). Structural shifts in credit rating standards. *Journal of Finance*, **68** (6), 2435–2470.
- ASHCRAFT, A. B. and SCHUERMANN, T. (2008). Understanding the securitization of subprime mortgage credit. *Foundations and Trends in Finance*, **2** (3), 191–309.
- BAE, K. H., KANG, J.-K. and WANG, J. (2015). Does increased competition affect credit ratings? A reexamination of the effect of Fitch’s market share on credit ratings in the corporate bond market. *Journal of Financial and Quantitative Analysis*, **50**, 1011–1035.
- BAERISWYL, R. and CORNAND, C. (2016). The predominant role of signal precision in experimental beauty contests. *The BE Journal of Theoretical Economics*, **16** (1), 267–301.
- and — (2021). Double overreaction in beauty-contests with information acquisition: Theory and experiments. *Journal of Monetary Economics*, **118**, 432–445.
- BAGHAI, R. P. and BECKER, B. (2020). Reputations and credit ratings: Evidence from commercial mortgage-backed securities. *Journal of Financial Economics*, **135**, 425–444.
- BANNIER, C. E. and & HIRSCH, C. W. (2010). The economic function of credit rating agencies – What does the watchlist tell us? *Journal of Banking & Finance*, **34** (12), 3037–3049.
- BAR-ISAAC, H. and SHAPIRO, J. (2013). Ratings quality over the business cycle. *Journal of Financial Economics*, **108**, 62–78.
- BAYONA, A. and PEIA, O. (2022). Financial contagion and the wealth effect: An experimental study. *Journal of Economic Behavior & Organization*, **200**, 1184–1202.
- BECKER, B. and MILBOURN, T. (2011). How did increased competition affect credit ratings? *Journal of Financial Economics*, **101** (3), 493–514.
- BENMELECH, E. and DLUGOSZ, J. (2009a). The alchemy of CDO credit ratings. *Journal of Monetary Economics*, **56**, 617–634.
- and — (2009b). The credit rating crisis. *NBER Working paper*, (15045).

- BLOOMFIELD, R. and ANDERSON, A. (2010). Experimental finance. *Behavioral Finance: Investors, Corporations, and Markets*, John Wiley & Sons, Inc, Hoboken, NJ, USA, pp. 113–130.
- BOLTON, P., FREIXAS, X. and SHAPIRO, J. (2012). The credit ratings game. *Journal of Finance*, **67** (1), 85–111.
- BOND, P., EDMANS, A. and GOLDSTEIN, I. (2012). The real effects of financial markets. *Annu. Rev. Financ. Econ.*, **4** (1), 339–360.
- BONGAERTS, D., CREMERS, K. M. and GOETZMANN, W. N. (2012). Tiebreaker: Certification and multiple credit ratings. *Journal of Finance*, **67** (1), 113–152.
- BOOT, A. W., MILBOURN, T. T. and SCHMEITS, A. (2006). Credit ratings as coordination mechanisms. *Review of Financial Studies*, **19** (1), 81–118.
- BOSSAERTS, P. *et al.* (2009). The experimental study of asset pricing theory. *Foundations and Trends® in Finance*, **3** (4), 289–361.
- BROWN, M., TRAUTMANN, S. T. and VLAHU, R. (2017). Understanding bank-run contagion. *Management Science*, **63** (7), 2272–2282.
- CABRALES, A., NAGEL, R. and ARMENTER, R. (2007). Equilibrium selection through incomplete information in coordination games: An experimental study. *Experimental Economics*, **10** (3), 221–234.
- CARLSSON, H. and VAN DAMME, E. (1993). Global games and equilibrium selection. *Econometrica*, **61** (5), 989–1018.
- CORNAGGIA, J. and CORNAGGIA, K. J. (2013). Estimating the Costs of Issuer-Paid Credit Ratings. *Review of Financial Studies*, **26** (9), 2229–2269.
- , — and ISRAELEN, R. D. (2018). Credit ratings and the cost of municipal financing. *Review of Financial Studies*, **31** (6), 2038–2079.
- CORNAND, C. and HEINEMANN, F. (2014a). Experiments on monetary policy and central banking. In *Experiments in macroeconomics*, Emerald Group Publishing Limited.
- and — (2014b). Measuring agents’ reaction to private and public information in games with strategic complementarities. *Experimental Economics*, **17** (1), 61–77.
- DALEY, B., GREEN, B. and VANASCO, V. (2020). Securitization, ratings, and credit supply. *Journal of Finance*, **75** (2), 1037–1082.
- DAVE, C., ECKEL, C. C., JOHNSON, C. A. and ROJAS, C. (2010). Eliciting risk preferences: When is simple better? *Journal of Risk and Uncertainty*, **41** (3), 219–243.

- DONALDSON, J. and PIACENTINO, G. (2018). Contracting to compete for flows. *Journal of Economic Theory*, **173**, 289–319.
- ECKEL, C. C. and GROSSMAN, P. J. (2008). Forecasting risk attitudes: An experimental study using actual and forecast gamble choices. *Journal of Economic Behavior & Organization*, **68** (1), 1–17.
- ELLUL, A., JOTIKASTHIRA, C. and LUNDBLAD, C. (2011). Regulatory pressure and fire sales in the corporate bond market. *Journal of Financial Economics*, **101** (3), 596–620.
- FISCHBACHER, U. (2007). z-tree: Zurich toolbox for ready-made economic experiments. *Experimental Economics*, **10** (2), 171–178.
- FRECHETTE, G. (2015). Laboratory experiments: professionals versus students. In: Fréchette, G.R., Schotter, A. (Eds.), *Handbook of Experimental Economic Methodology*. Oxford University Press, pp. 360–390.
- FRENKEL, S. (2015). Repeated interaction and rating inflation: A model of double reputation. *American Economic Journal: Microeconomics*, **7** (1), 250–280.
- FULGHIERI, P., STROBL, G. and XIA, H. (2014). The economics of solicited and unsolicited credit ratings. *Review of Financial Studies*, **27** (2), 484–518.
- GÄCHTER, S., JOHNSON, E. J. and HERRMANN, A. (2022). Individual-level loss aversion in riskless and risky choices. *Theory and Decision*, **92** (3), 599–624.
- GAO, P. (2008). Keynesian beauty contest, accounting disclosure, and market efficiency. *Journal of Accounting Research*, **46** (4), 785–807.
- GOEL, A. M. and THAKOR, A. V. (2015). Information reliability and welfare: A theory of coarse credit ratings. *Journal of Financial Economics*, **115** (3), 541–557.
- GOLDSTEIN, I. (2023). Information in financial markets and its real effects. *Review of Finance*, **27** (1), 1–32.
- and HUANG, C. (2020). Credit rating inflation and firms’ investments. *Journal of Finance*, **75** (6), 2929–2972.
- GRIFFIN, J., NICKERSON, J. and TANG, D. Y. (2013). Rating shopping or catering? An examination of the response to competitive pressure for cdo credit ratings. *Review of Financial Studies*, **26**, 2270–2310.
- and TANG, D. Y. (2011). Did credit rating agencies use biased assumptions? *American Economic Review*, **101**, 125–130.
- and — (2012). Did subjectivity play a role in CDO credit ratings? *Journal of Finance*, **67** (4), 1293–1328.

- HE, J., QIAN, J. and STRAHAN, P. (2012). Are all ratings created equal? The impact of issuer size on the pricing of mortgage-backed securities. *Journal of Finance*, **67**, 2097–2137.
- HE, Z. and XIONG, W. (2012). Dynamic debt runs. *The Review of Financial Studies*, **25** (6), 1799–1843.
- HEINEMANN, F., NAGEL, R. and OCKENFELS, P. (2004). The theory of global games on test: Experimental analysis of coordination games with public and private information. *Econometrica*, **72** (5), 1583–1599.
- , — and — (2009). Measuring strategic uncertainty in coordination games. *Review of Economic Studies*, **76** (1), 181–221.
- HIRTH, S. (2014). Credit rating dynamics and competition. *Journal of Banking & Finance*, **49**, 100–112.
- HUCK, S. and MULLER, W. (2012). Allais for all: revisiting the paradox in a large representative sample. *Journal of Risk and Uncertainty*, **44**, 261–293.
- , NORMANN, H.-T. and OECHSSLER, J. (2004). Two are few and four are many: number effects in experimental oligopolies. *Journal of economic behavior & organization*, **53** (4), 435–446.
- JEON, D.-S. and LOVO, S. (2013). Credit rating industry: A helicopter tour of stylized facts and recent theories. *International Journal of Industrial Organization*, **31**, 643–651.
- JIANG, J., STANFORD, M. and XIE, Y. (2012). Does it matter who pays for bond ratings? Historical evidence. *Journal of Financial Economics*, **105** (3), 607–621.
- KESER, C., ÖZGÜMÜS, A., PETERLÉ, E. and SCHMIDT, M. (2017). An experimental investigation of rating-market regulation. *Journal of Economic Behavior & Organization*, **144**, 78–86.
- KISGEN, D. (2009). Do firms target credit ratings or leverage levels? *Journal of Financial and Quantitative Analysis*, **44** (6), 1323–1344.
- and STRAHAN, P. (2010). Do regulations based on credit ratings affect a firm’s cost of capital? *Review of Financial Studies*, **23** (12), 4324–4347.
- KISS, H. J., RODRIGUEZ-LARA, I. and ROSA-GARCIA, A. (2018). Panic bank runs. *Economics Letters*, **162**, 146 – 149.
- KLIGER, D. and SARIG, O. (2000). The information value of bond ratings. *Journal of Finance*, **55** (6), 2879–2902.
- LEVY, H. (1994). Absolute and relative risk aversion: An experimental study. *Journal of Risk and Uncertainty*, **8**, 289–307.

- MÄHLMANN, T. (2011). Is there a relationship benefit in credit ratings? *Review of Finance*, **15** (3), 475–510.
- MANSO, G. (2013). Feedback effects of credit ratings. *Journal of Financial Economics*, **109**, 535–548.
- MORRIS, S. and SHIN, H. S. (1998). Unique equilibrium in a model of self-fulfilling currency attacks. *American Economic Review*, **88** (3), 587–597.
- and — (2004). Coordination risk and the price of debt. *European Economic Review*, **48** (1), 133–153.
- MY, K. B., CORNAND, C. and FERREIRA, R. D. S. (2021). Public information and the concern for coordination. *Journal of Behavioral and Experimental Economics*, **93**, 101710.
- NOUSSAIR, C., TRAUTMANN, S. and VAN DE KUILEN, G. (2014). Higher order risk attitudes, demographics, and financial decisions. *Review of Economic Studies*, **81**, 325–355.
- OPP, C. C., OPP, M. M. and HARRIS, M. (2013). Rating agencies in the face of regulation. *Journal of Financial Economics*, **108** (1), 46–61.
- PARLOUR, C. A. and RAJAN, U. (2020). Contracting on credit ratings: Adding value to public information. *Review of Financial Studies*, **33** (4), 1412–1444.
- PEIA, O. and VRANCEANU, R. (2019). Experimental evidence on bank runs with uncertain deposit coverage. *Journal of Banking & Finance*, **106**, 214–226.
- RABANAL, J. P. and RUD, O. A. (2017). Does competition affect truth telling? An experiment with rating agencies. *Review of Finance*, **22** (4), 1581–1604.
- SANGIORGI, F. and SPATT, C. (2017). The economics of credit rating agencies. *Foundations and Trends in Finance*, **12** (1), 1–116.
- SANJAY, B. and MAIER, M. (2016). Public information precision and coordination failure: An experiment. *Journal of Accounting Research*, **54** (4), 941–986.
- SHURCHKOV, O. (2016). Public announcements and coordination in dynamic global games: Experimental evidence. *Journal of Behavioral and Experimental Economics*, **61**, 20–30.
- SKRETA, . V. L., V. (2009). Ratings shopping and asset complexity: A theory of ratings inflation. *Journal of Monetary Economics*, **56** (5), 678–695.
- STROBL, G. and XIA, H. (2012). The issuer-pays rating model and ratings inflation: Evidence from corporate credit ratings. *Available at SSRN 2002186*.
- SUFI, A. (2009). The real effects of debt certification: Evidence from the introduction of bank loan ratings. *Review of Financial Studies*, **22** (4), 1659–1691.

- SUNDER, S. (2007). What have we learned from experimental finance? In *Developments on Experimental Economics*, Springer, pp. 91–100.
- SZKUP, M. and TREVINO, I. (2020). Sentiments, strategic uncertainty, and information structures in coordination games. *Games and Economic Behavior*, **124**, 534–553.
- TANG, T. T. (2009). Information asymmetry and firms’ credit market access: Evidence from Moody’s credit rating format refinement. *Journal of Financial Economics*, **93** (2), 325–351.
- TEROVITIS, S. (2020). Information disclosure and the feedback effect in capital markets. *Journal of Financial Intermediation*, p. 100897.
- US GOVERNMENT, U. (2011). Financial crisis inquiry commission. Available online: http://fcic-static.law.stanford.edu/cdn_media/fcic-reports/fcic_final_report_conclusions.pdf.
- US SENATE, U. (2007). The role and impact of credit rating agencies in the subprime credit markets. *Senate Hearing 110-931 September 26*.
- WEBER, M., DUFFY, J. and SCHRAM, A. (2018). An experimental study of bond market pricing. *Journal of Finance*, **73** (4), 1857–1892.
- WEITZEL, U., HUBER, C., HUBER, J., KIRCHLER, M., LINDLER, F. and ROSE, J. (2020). Bubbles and financial professionals. *Review of Financial Studies*, **33**, 2659–2696.
- WHITE, L. (2010). Markets: The credit rating agencies. *Journal of Economic Perspectives*, **24** (2), 211–226.
- WHITE, L. J. (2013). Credit rating agencies: An overview. *Annu. Rev. Financ. Econ.*, **5** (1), 93–122.

Appendix

A Theoretical predictions

In this section, we provide more technical details of the theoretical predictions presented in the main text by writing them formally and deriving proofs based on the work of [Goldstein and Huang \(2020\)](#).

A.1 Equilibrium without a CRA

We start by outlining the equilibrium in a benchmark model without a rating agency. The equilibrium concept is a monotone perfect Bayesian equilibrium. We solve the model backwards. First, we derive the firm's optimal investment strategy at date 1, conditional on θ , by using the firm's expected profits in (3) and then deriving the firm's profit-maximizing strategy. The firm always has the incentive to choose the LR project over the HR project for $K(\theta) \geq I$ since $p[V - I + K(\theta) - W(\theta)F] > q[H - W(\theta)F + K(\theta)]$.³⁶ When the available funds are positive, but not sufficient to allow investment in the LR project (i.e., $0 < K(\theta) < I$), choosing the HR project dominates the decision to default since $q[H - W(\theta)F + K(\theta)] > 0$.³⁷ Therefore, the firm's optimal investment strategy at date 1, conditional on the total available funding, $K(\theta) = \theta + W(\theta)B$, is as follows:

$$\left\{ \begin{array}{ll} \text{Invest in LR project} & \text{if } K(\theta) \geq I \\ \text{Invest in HR project} & \text{if } 0 \leq K(\theta) < I. \\ \text{Default} & \text{if } K(\theta) < 0. \end{array} \right. \quad (6)$$

Equation (6) implies that a firm would choose to default when the total funds available from bonds markets and the ongoing project are low enough. This happens when $\theta < \tilde{\theta}_1$, where

³⁶One can verify that this is equivalent to $K(\theta) > W(\theta)F - ((p(V - I) - qH)/(p - q))$. For $K(\theta) \geq I$ it is sufficient to show that $I > W(\theta)F - (p(V - I) - qH)/(p - q)$, which holds given that $I > F$ and $pV - I > qH$ by assumption.

³⁷The inequality holds since $H > F$.

$\tilde{\theta}_1$ solves:

$$K(\tilde{\theta}_1) = \tilde{\theta}_1 + W(\tilde{\theta}_1) B = 0. \quad (7)$$

As $K(\theta)$ is strictly increasing in θ , for any $\theta < \tilde{\theta}_1$ the firm's external funding is insufficient to cover the losses from the ongoing project. However, when $\theta > \tilde{\theta}_1$, the firm has incentives to invest in a new project. The firm chooses the LR project over the HR project for $\theta \geq \tilde{\theta}_2$, where $\tilde{\theta}_2$ solves:

$$K(\tilde{\theta}_2) = \tilde{\theta}_2 + W(\tilde{\theta}_2) B = I. \quad (8)$$

Next, we solve for investors' optimal investment actions. Given θ , the realization of fundamentals, and the investors' threshold strategies, the measure of investors who buy the bond is:

$$W(\theta) = \Pr(x \geq \tilde{x}|\theta) = 1 - \Pr(x < \tilde{x}|\theta) = 1 - \frac{\tilde{x} - \theta + \epsilon}{2\epsilon} = \frac{\theta - \tilde{x} + \epsilon}{2\epsilon}, \quad (9)$$

following from the fact that signals are uniformly distributed over $[\theta - \epsilon, \theta + \epsilon]$.

Furthermore, an investor has a dominant strategy to invest when the expected payoff of doing so, conditional on the available information, is higher than the expected payoff of not investing. Any investor j receiving a signal x_j invests as long as her signal is higher than the threshold signal, $\tilde{x}$. As such, there must be a marginal investor who receives exactly the signal $\tilde{x}$ and is indifferent between buying or not the bond. The indifference condition is such that:

$$\text{Prob}[\theta \geq \tilde{\theta}_2 | \tilde{x}] \times pF + \left\{ \text{Prob}[\theta < \tilde{\theta}_2 | \tilde{x}] - \text{Prob}[\theta < \tilde{\theta}_1 | \tilde{x}] \right\} \times qF = B, \quad (10)$$

where the first term of the left-hand side is the expected payoff on the LR project (the firm undertakes the LR project with the probability that θ is above $\tilde{\theta}_2$ and investors receive F with probability p), while the second term is the expected payoff on the HR project (the firm undertakes the HR project with the probability that θ is between $[\tilde{\theta}_1, \tilde{\theta}_2]$ and creditors receive F with probability q). We can now prove Theoretical prediction 1.

Proof of Theoretical prediction 1

To find the unique equilibrium thresholds $(\tilde{\theta}_1, \tilde{\theta}_2, \tilde{x})$ in the benchmark model without a CRA we need to show that there is a unique solution to equations (7), (8), and (10), which can be re-written as follows:

$$\begin{cases} \tilde{\theta}_1 + \left(\frac{\tilde{\theta}_1 - \tilde{x} + \epsilon}{2\epsilon} \right) B = 0 \\ \tilde{\theta}_2 + \left(\frac{\tilde{\theta}_2 - \tilde{x} + \epsilon}{2\epsilon} \right) B = I \\ \left(\frac{\tilde{x} - \tilde{\theta}_2 + \epsilon}{2\epsilon} \right) pF + \left(\frac{\tilde{\theta}_2 - \tilde{x} + \epsilon}{2\epsilon} - \frac{\tilde{\theta}_1 - \tilde{x} + \epsilon}{2\epsilon} \right) qF = B, \end{cases}$$

where we have used the fact that the posterior belief over the firm fundamentals when observing a signal $\tilde{x}$ is uniformly distributed over $[\tilde{x} - \epsilon, \tilde{x} + \epsilon]$. The system of equations with three unknowns has the following solution:

$$\begin{cases} \tilde{x} = \frac{B(2\epsilon + B)}{pF} + \frac{(p-q)I}{p} - (\epsilon + B) \\ \tilde{\theta}_1 = \frac{\tilde{x} - \epsilon}{\frac{2\epsilon}{B} + 1} \\ \tilde{\theta}_2 = \frac{\tilde{x} - \epsilon + \frac{2\epsilon I}{B}}{\frac{2\epsilon}{B} + 1} \end{cases}$$

As $\frac{2\epsilon I}{B + 2\epsilon} > 0$, we obtain that $\tilde{\theta}_2 > \tilde{\theta}_1$. *QED*

A.2 Equilibrium with a CRA

We follow [Goldstein and Huang \(2020\)](#) and make several assumptions about the CRA's payoff function in order to derive conditions under which the CRA has an incentive to assign an inflated rating. Specifically, the payoff function of the CRA is as follows: it earns a revenue S^R and faces a potential cost C^R when assigning a rating $R = p, q$. In line with the “issuer-pays” business model, we assume that the CRA receives higher revenues when assigning better credit ratings: $S^p > S^q > 0$.³⁸ The cost C^R corresponds to (exogenous) reputation or

³⁸See [Bar-Isaac and Shapiro \(2013\)](#) and [Sangiorgi and Spatt \(2017\)](#) for a discussion of the relationship between reputational incentives and credit quality and the frictions associated with CRAs.

legal costs in the case of firm default. We assume that if a firm with rating $R > 0$ defaults at $t = 1$, the reputational costs for the CRA are very large ($C^{\text{early default}} > S^p$), such that the CRA does not assign a rating to firms it foresees defaulting at $t = 1$. If a firm with rating $R > 0$ defaults at $t = 2$, the CRA incurs a cost C^R ($R = p, q$), with $S^p > S^q > C^p > C^q > 0$.

Lemma 1 If $S^p - S^q \geq (1 - q)(C^p - C^q)$, the equilibrium strategy of the CRA is to assign an inflated rating, as follows:

$$R(\theta) = \begin{cases} p & \text{if } \theta \geq \theta_1^* \\ 0 & \text{if } \theta < \theta_1^*. \end{cases} \quad (11)$$

Proof of Lemma 1 To prove Lemma 1 we need to show that the CRA will not assign a rating q in equilibrium, whenever $\frac{S^p - S^q}{C^p - C^q} \geq 1 - q$ holds. Suppose the CRA assigns a rating q to a θ -firm when $\theta \in (\theta_1, \theta_2)$. We will show that it is always profitable for the CRA to deviate and assign a rating p .

Consider the case in which investors believe that a rating p implies that the firm has better fundamentals than a firm with rating q . In that case, if the CRA deviates and assigns a rating p , more investors will buy the firm's bonds. This implies that if the firm does not default with a rating of q , it won't default when the CRA assigns a rating of p either. At the same time, the condition $\frac{S^p - S^q}{C^p - C^q} \geq 1 - q$ implies that:

$$\frac{S^p - S^q}{C^p - C^q} \geq 1 - q \geq 1 - p, \text{ since } p > q. \quad (12)$$

If the firm invests in the HR project when assigned a rating p , the CRA obtains a profit of $S^p - (1 - q)C^p$. From (12) we obtain that $S^p - (1 - q)C^p > S^q - (1 - q)C^q$, implying that the CRA is better off by deviating and assigning a rating p even if the firm invests in an HR project and defaults with probability $1 - q$. Likewise, if the firm invests in an LR project, the CRA's profit is $S^p - (1 - p)C^p$ and using (12) we obtain that $S^p - (1 - p)C^p > S^q - (1 - p)C^q$, implying that it is more profitable for the CRA to deviate and assign rating p .

Consider now the case in which investors do not believe that a rating p implies that the

firm has better fundamentals than a firm with rating q . Then there are some intervals of fundamentals where the rating is p for $\theta \in (\theta_3, \theta_4)$ and q for $\theta \in (\theta_1, \theta_2)$, with $\theta_3 < \theta_4 < \theta_1 < \theta_2$. If the CRA deviates and assigns a firm with fundamentals in interval (θ_1, θ_2) a rating of p instead of q , investors will believe that the fundamentals are worse, i.e., in interval (θ_3, θ_4) . However, firms in neither (θ_1, θ_2) nor (θ_3, θ_4) intervals will default early (as the CRA never assigns a rating different from zero to firms that it believes will default early). So firms with fundamentals in interval (θ_1, θ_2) will not default early even if they receive a rating p . Given that from (12) the CRA has higher expected profits when assigning a rating p , the CRA will then deviate and prefer to assign a rating p .

Summing up the two cases, there is no equilibrium in which the CRA assigns a rating q when (12) holds. *QED*

Proof of Theoretical prediction 2

In the model with a CRA, the equilibrium is described by $(\theta_1^*, \theta_2^*, x^*)$, with the CRA assigning a rating $R = p$ if $\theta \geq \theta_1^*$, and $R = 0$ otherwise (see Lemma 1). When $R = 0$, no investor buys bonds, whereas, for $R = p$, investors buy the bonds if and only if their private signals x are larger than x^* , where x^* is obtained from the indifference condition of the marginal investor

$$\left(\frac{\text{Prob}[\theta \geq \theta_2^* \mid x^*]}{\text{Prob}[\theta \geq \theta_1^* \mid x^*]} \right) pF + \left(\frac{\text{Prob}[\theta < \theta_2^* \mid x^*] - \text{Prob}[\theta < \theta_1^* \mid x^*]}{\text{Prob}[\theta \geq \theta_1^* \mid x^*]} \right) qF = B. \quad (13)$$

The firm invests in the HR project if $\theta_1^* \leq \theta < \theta_2^*$ and undertakes the LR project if $\theta \geq \theta_2^*$, where θ_1^* solves

$$K(\theta_1^*) = \theta_1^* + W(\theta_1^*)B = 0, \quad (14)$$

and θ_2^* solves

$$K(\theta_2^*) = \theta_2^* + W(\theta_2^*)B = I. \quad (15)$$

Using the fact that $W(\theta) = \frac{\theta - \hat{x} + \epsilon}{2\epsilon}$, equations (13), (14), and (15) in Theoretical Prediction

2 becomes:

$$\begin{cases} \theta_1^* + \left(\frac{\theta_1^* - \tilde{x} + \epsilon}{2\epsilon} \right) B = 0 \\ \theta_2^* + \left(\frac{\theta_2^* - \tilde{x} + \epsilon}{2\epsilon} \right) B = I \\ \frac{(x^* - \theta_2^* + \epsilon)pF + (\theta_2^* - \theta_1^*)qF}{x^* - \theta_1^* + \epsilon} = B. \end{cases}$$

The unique solution $(x^*, \theta_1^*, \theta_2^*)$ to the previous system of equations is:

$$\begin{cases} x^* = \frac{(p-q)IF}{pF-B} - (\epsilon + B) \\ \theta_1^* = \frac{x^* - \epsilon}{\frac{2\epsilon}{B} + 1} \\ \theta_2^* = \frac{x^* - \epsilon + \frac{2\epsilon I}{B}}{\frac{2\epsilon}{B} + 1}. \end{cases}$$

Since $\frac{2\epsilon I}{B+2\epsilon} > 0$, we obtain that $\theta_2^* > \theta_1^*$. *QED*

A.3 Numerical calculations of equilibrium

In this section, we illustrate how we derive the thresholds for the benchmark model. Using the parametrization in Table 1, and the fact that, with a finite number of players, the expected number of investors who buy the bond is given by $E[W(\theta)] = n \Pr(x_j \geq x^*|\theta) = n \left(\frac{\tilde{\theta}_1 - \tilde{x} + \epsilon}{2\epsilon} \right)$. Then, we compute the equilibrium thresholds, $\tilde{\theta}_1$ and $\tilde{\theta}_2$, as follows:

$$\begin{cases} \tilde{\theta}_1 + n \left(\frac{\tilde{\theta}_1 - \tilde{x} + \epsilon}{2\epsilon} \right) B = 0 \\ \tilde{\theta}_2 + n \left(\frac{\tilde{\theta}_2 - \tilde{x} + \epsilon}{2\epsilon} \right) B = I \\ \left(\frac{\tilde{x} - \tilde{\theta}_2 + \epsilon}{2\epsilon} \right) pF + \left(\frac{\tilde{\theta}_2 - \tilde{x} + \epsilon}{2\epsilon} - \frac{\tilde{\theta}_1 - \tilde{x} + \epsilon}{2\epsilon} \right) qF = B. \end{cases}$$

The solutions to this system of equations are $\tilde{\theta}_1 = -13$ and $\tilde{\theta}_2 = 18$, and are shown in Figure 1. We follow analogous calculations to derive θ_1^* and θ_2^* .

Appendix B: Additional empirical results

Table 9: Average number of investors and fundamentals

Fundamental	Baseline (1)	CRA (2)	Test 1 (3)	Test 2 (4)
1st quartile	0.38 (0.55)	0.20 (0.44)	0.00	0.03
2nd quartile	0.95 (1.06)	0.43 (0.68)	0.00	0.00
3rd quartile	2.98 (1.38)	3.27 (1.53)	0.07	0.39
4th quartile	4.57 (0.71)	4.70 (0.57)	0.07	0.22

Notes: Columns (1)-(2) present the mean (standard deviation) of the number of subjects (per group) investing, conditional on the treatment and quartiles of firm fundamentals. Test 1 in column (3) is a t-test of equality of means at the group level. Test 2 in column (4) is the Mann-Whitney U non-parametric test performed at the session level. Quartile 1 corresponds to $IF \in [-400, -222]$, Quartile 2 to $IF \in [-221, -62]$, Quartile 3 to $IF \in [-61, 19]$, and Quartile 4 to $IF \in [20, 200]$.

Table 10: Ratings and firms' actions: marginal effects

	(1) Bad rating (B) Default	(2) Low risk	(3) Good rating (A) Default	(4) Low risk
<i>Baseline outcome: High Risk</i>				
CRA treatment	0.0939*** (3.62)	-0.0921** (-2.23)	-0.0888* (-1.93)	0.110** (2.66)
Observations	735	735	600	600

Notes: The table reports estimates from multinomial logit regressions where the dependent variable is the firm action: default, high-risk project, and low-risk project. Reported coefficients are the marginal effects (dy/dx), representing the change in the probability of choosing a given action relative to the high-risk project. Columns (1) and (3) present the marginal effects for default relative to the high-risk project, while columns (2) and (4) report the effects for choosing the low-risk project relative to the high-risk project. Results are shown separately for values of fundamentals corresponding to a Bad rating (B), i.e., values below -31 in columns (1)-(2), and a Good rating (A), i.e., values above -31 in columns (3)-(4). The baseline category is the high-risk project. Constant terms, a period scalar, and internal funds (IF) are included in the regressions but not reported. Standard errors, clustered at the session level, are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.