

Lending to Overconfident Borrowers

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Abstract

We study credit market outcomes for overconfident borrowers, exploiting variation in pupils' overconfidence in mathematics across Italian provinces. Managers born in overconfident provinces make larger forecast errors on future sales, pay higher loan rates, and obtain smaller loans. Consistent with a credit market model in which borrowers have biased beliefs, access to collateralized lending relaxes the financial constraints of overconfident borrowers, leading them to borrow and invest more—yet default more frequently. We estimate that bad loans in Italy would have been 6% lower had banks relied less on collateral when lending to overconfident borrowers.

Keywords: overconfidence; collateral; banks; credit; investment; default.

JEL: G21

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1 Introduction

Entrepreneurs and top executives tend to be overconfident in their managerial abilities and overestimate the chances of success for their businesses. Several studies have explored the implications of managerial overconfidence for a number of corporate decisions, such as investment, acquisitions, and debt maturity (Malmendier and Tate, 2005, 2008; Landier and Thesmar, 2008; Ben-David et al., 2013). However, there is less evidence on how borrowers' overconfidence affects credit outcomes, such as borrowing amounts and loan rates, which may have significant economic implications given the amplifying role of leverage and the potential distortions associated with overconfidence.¹

Investigating the effects of borrowers' overconfidence on credit outcomes poses two main empirical challenges. First, overconfidence is likely to be endogenous to other unobserved factors. Managers' forecast errors may reflect not only overconfidence but also unexpected negative shocks that induce rational errors. Second, if overconfident borrowers invest in value-destroying projects (Malmendier and Tate, 2008), their credit outcomes may be difficult to distinguish from those of ex-ante risky borrowers. In this paper, we address both challenges by combining micro-level data from the Italian Credit Register with province-level measures of overconfidence derived from the national education test. We provide novel evidence on the impact of borrowers' overconfidence on credit outcomes and its implications for corporate investment and default.

First, to guide our empirical investigation, we formulate a simple model of bank lending to overconfident borrowers. Following prior work (Manove and Padilla, 1999; Landier and Thesmar, 2008), we assume that overconfident borrowers always perceive their projects as having positive net present value (NPV). We show that their credit outcomes depend on the availability of collateralized lending. While collateral is typically viewed as mitigating asymmetric information problems in credit markets (Bester, 1985; Besanko and Thakor,

¹Previous work on financial contracting with overconfident or optimistic managers is mostly theoretical (e.g., de Meza and Southey, 1996; Heaton, 2002; Coval and Thakor, 2005). Adam et al. (2020) and Lin et al. (2020) offer empirical evidence of the effect of CEO overconfidence on loan spreads and covenants.

1987), our model highlights that requiring collateral from overconfident borrowers who, by definition, underestimate the risks they take can instead lead to over-borrowing and higher default. In particular, overconfident borrowers are credit-rationed by non-collateral-based banks, that is, banks that on average do not rely on collateralized lending, but can borrow from collateral-based banks when they possess sufficient pledgeable assets. The model yields three testable implications that guide our empirical analysis. First, access to collateralized lending relaxes the financial constraints of overconfident borrowers. Second, by relaxing these constraints, collateralized lending leads overconfident borrowers to invest more than realistic borrowers. Third, collateralized lending raises ex-post default among overconfident borrowers.

We then turn to our empirical analysis. To identify the effect of overconfidence on credit outcomes, we exploit variation across Italian provinces in the share of local pupils who find mathematics easier than their classmates in the Italian national education test (INVALSI). We do not interpret this measure as identifying the primitive sources of overconfidence; rather, we use it as a proxy for persistent local variation in overconfidence that is informative about managerial beliefs later in life. Previous studies show that historical or cultural factors, such as ethnicity, customs, and local traditions, can shape current beliefs and attitudes (Guiso et al., 2016; D’Acunto et al., 2019; Michalopoulos and Xue, 2021). If beliefs are partly a local cultural trait, then pupils’ overconfidence should capture persistent differences in beliefs among individuals born in the same province. Using pupils’ overconfidence as opposed to managers’ forecast errors allows us to identify the effect of overconfidence on credit outcomes because pupils’ self-reported ability is plausibly unrelated to economic shocks. A potential concern, however, is that another unobserved local factor may still drive our results. To address it, we restrict our attention to “movers” (i.e., managers born in a different province from the one the firm is located in). If expectations are shaped by early-life experiences, which in turn depend on location (Malmendier and Nagel, 2011), then overconfidence in the manager’s province of birth should predict managerial beliefs later in life. This strategy allows us to include province-year fixed effects for the firm’s current location, thereby absorbing

time-varying shocks in the local environment where the firm operates.

We first show that pupils’ overconfidence at the province level is not correlated with other risk and social preferences (Falk et al., 2018), local economic development, law inefficiency, and social capital (Guiso et al., 2004) once macro-area indicators are included.² Then, using confidential firm-level survey data from the Bank of Italy, we document a robust relationship between pupils’ overconfidence and managers’ optimistic forecasts of their future sales growth. A borrower born in a province with the highest level of overconfidence has a 36% higher probability of making a large positive forecast error compared to a borrower from the least overconfident province. We saturate the regression with an extensive set of industry-year and credit score-year fixed effects to absorb time-varying unobserved shocks that may also cause forecast errors to be higher.

We then investigate the effects of borrowers’ overconfidence on credit outcomes, using Italian Credit Register data on collateralized credit, interest rates, and credit volumes. We find that moving from the lowest to the highest level of overconfidence is associated with loan rates that are 40 basis points higher, and 6.6% lower credit amounts. Next, we examine whether collateral mitigates or reinforces the credit constraints faced by overconfident borrowers. We begin with a simple approach, interacting overconfidence with the lagged firm-level share of credit backed by collateral. We find that collateral substantially attenuates the credit gap: a one-standard-deviation increase in the share of collateralized credit reduces the difference in credit volumes between low- and high-overconfidence borrowers by about 45%. Because collateral is an equilibrium outcome and may be endogenous to unobserved firm characteristics, we next isolate both lender-side and borrower-side sources of variation.

On the lender side, we follow a methodology similar to Amiti and Weinstein (2018). Specifically, we regress the share of collateralized credit on both firm-year and bank-year fixed effects, and interpret the latter as a measure of banks’ reliance on collateral, net of

²Macro-area indicators are dummies for the North and South of Italy. The South is characterized by low levels of social capital and trust, low income levels, and poor legal enforcement. Provinces are geographical units that surround a large city, similar to an MSA in the United States. There are 110 provinces in Italy in 2005-2017.

firm-specific demand for collateralized loans. Using this measure, we obtain results confirming that collateral relaxes credit constraints for overconfident borrowers: a one-standard-deviation increase in banks' propensity to require collateral reduces the credit gap between low- and high-overconfidence borrowers by about 44%. On the borrower side, we exploit instead sectoral differences in the pledgeability of assets by interacting overconfidence with asset tangibility at the industry-year level. In line with the predictions of our model, we find that firms with more tangible assets, which are easier to pledge (Rajan and Zingales, 1995; Almeida and Campello, 2007), face weaker credit constraints when their managers are more overconfident; quantitatively, a one-standard-deviation increase in asset tangibility reduces the credit gap by about 29%.

We also explore the real implications of our findings for corporate investment and default. Previous studies document that overconfident managers invest more than rational managers (Malmendier and Tate, 2005; Goel and Thakor, 2008; Ben-David et al., 2013). Our novel contribution is to show that the sensitivity of investment to overconfidence is amplified by the collateral lending channel: overconfident borrowers exhibit a higher investment rate when exposed to lenders that rely more on collateral. Quantitatively, a one-standard-deviation increase in banks' reliance on collateral raises the investment rate of high- relative to low-overconfidence borrowers by about 0.4 percentage points (around 7% of the sample mean). Crucially, the results hold controlling for ex-ante borrowers' credit risk. We thus provide insights on the role of banks in shaping how managers' overconfidence affects economic outcomes.

Finally, we estimate the loan losses that could have been avoided if banks did not rely on collateral when lending to overconfident borrowers. We find that non-performing bad loans would be €6.7 billion (6%) lower in Italy in 2017 if banks had relied less on collateral when lending to overconfident borrowers. Since average recovery rates on bad loans to non-financial firms are 36%, the majority of banks do not fully recover the value of the loan when the borrower is in distress. These results suggest that the collateral lending channel matters

quantitatively and helps explain the aggregate economic impact of overconfidence.

Our findings contribute to several strands of the literature. First, we build on a large body of work on the effect of biased expectations on a series of firm-level outcomes, including investment (Malmendier and Tate, 2005; Ben-David et al., 2013), leverage (Malmendier et al., 2011, 2023), risk-taking and innovation (Galasso and Simcoe, 2011; Hirshleifer et al., 2012), and firm value (Malmendier and Tate, 2008; Barrero, 2022).³ There is also a fast-growing literature on the implications of biased beliefs in the time series, especially in the context of credit booms (e.g., Greenwood and Hanson, 2013; Fahlenbrach et al., 2018; Bordalo et al., 2018; Ma et al., 2020; Carvalho et al., 2023). Although our analysis is cross-sectional, our findings also speak to this literature: when borrower overconfidence grows, collateralized lending may facilitate risk-taking and thereby amplify credit cycles.

There are several theoretical studies that examine financial contracting with managers holding biased beliefs (e.g., de Meza and Southey, 1996; de Meza, 2002; Heaton, 2002; Coval and Thakor, 2005; Sandroni and Squintani, 2007; Hackbarth, 2008). Landier and Thesmar (2008) show that French optimistic managers may naturally self-select into short-term debt. Using data from U.S. publicly listed firms, Otto (2014) finds that overconfident CEOs receive lower total compensation than their peers, Adam et al. (2020) document that they are more likely to select performance-sensitive loan contracts, and Lin et al. (2020) find that they pay lower loan spreads. Fecht and Opaleva (2021) use survey data on German SMEs and find that overconfident managers are more likely than others to report that their loan applications have been rejected. In our paper, we use credit register data and study the implications of borrowers' overconfidence and banks' collateral requirements for credit allocation.

Finally, our results provide novel insights on the benefits and costs of collateral in debt contracts. Collateral is a screening device that attenuates adverse selection ex-ante (Bester, 1985; Besanko and Thakor, 1987) and reduces ex-post frictions, such as moral hazard (Thakor and Udell, 1991; Boot and Thakor, 1994). Consistent with the predictions from ex-post

³Theoretically, a moderate level of overconfidence can be beneficial to firm value and investment (Goel and Thakor, 2008; Gervais et al., 2011).

theories, previous studies find that the incidence of collateral is positively related to observable borrower risk and interest rates (Berger and Udell, 1990; Kose et al., 2003; Jiménez et al., 2006; Brick and Palia, 2007; Berger et al., 2011) and that collateral requirements have a negative impact on the default probability of risky borrowers (Ioannidou et al., 2022). Our contribution is to provide novel empirical evidence on the distortionary effects of collateral for overconfident borrowers: by relaxing their financial constraints, collateralized lending leads them to borrow more, invest more, and experience higher default rates. Thus, rather than mitigating risk, collateral can reinforce excessive borrowing and investment by overconfident borrowers, highlighting a previously undocumented cost of collateral in the presence of biased expectations.

2 Theoretical Framework

In the psychology literature, the term overconfidence refers to at least three different notions: miscalibration, the illusion of control, and overplacement. Miscalibration, or overprecision, refers to excessive confidence about having accurate information (Oskamp, 1965), which results in individuals forming excessively narrow subjective probability distributions (e.g., Ben-David et al., 2013). The illusion of control is the tendency to overestimate how much control one has over uncontrollable events (e.g., Langer, 1975). Overplacement is instead the belief of being better than others, a notion that is also referred to as the “better-than-average” effect (Moore and Healy, 2008). In this paper, we refer to overconfidence in terms of overplacement, as in Malmendier and Tate (2005, 2008) for example.

According to theory, credit markets may be characterized by excessive lending when managers have overconfident beliefs about the future prospects of their firms (de Meza and Southey, 1996; de Meza, 2002). This is because overconfidence leads managers to often (wrongly) perceive negative NPV projects as being profitable (Heaton, 2002). Importantly, as shown in Manove and Padilla (1999), when borrowers have biased beliefs about their projects,

collateral can reduce credit market efficiency by inducing banks to lend to overconfident borrowers who then may invest in value-destroying projects. This is in sharp contrast with theoretical findings indicating that collateral typically mitigates lending frictions, such as adverse selection and moral hazard. In particular, when self-conscious risky borrowers are required to pledge collateral, this encourages a shift into safer investment projects, and lowers default probability (Ioannidou et al., 2022). Instead, collateral does not discipline overconfident borrowers, who by definition are not conscious of their own biases, and they end up investing and defaulting more when they receive credit.

2.1 Model of bank lending to overconfident borrowers

To guide our empirical investigation, we develop a simple model of bank lending to entrepreneurs who differ in their beliefs about project quality. Banks also differ in whether they rely on collateral, which crucially shapes outcomes when borrowers are overconfident. The model yields three testable implications: for overconfident borrowers, (i) access to collateral relaxes financial constraints, (ii) by relaxing these constraints, collateralized lending increases investment relative to realistic borrowers, and (iii) collateralized lending raises ex-post default.

The model. An entrepreneur has a project whose return depends on both: (i) the project’s type which can be bad (“B”) or good (“G”) with probabilities α and $1 - \alpha$; (ii) the investment level which can be either low (“L”) or high (“H”). The cost of an investment is proportional to its size and the returns of good (respectively bad) projects at low versus high levels of investment are denoted $R_{G,L}$ and $R_{G,H}$ (respectively $R_{B,L}$ and $R_{B,H}$). The entrepreneur has assets in place, A , which may serve as collateral in default, and looks for external financing from competitive banks. In this simple framework, the entrepreneur has no access to alternative investment projects and the size of the loan requested from the bank and the desired investment level coincide.

We assume that $R_{B,H} = 0 < R_{B,L} - L < R_{G,L} - L < R_{G,H} - H$. These assumptions imply that good projects at any level of investment have returns exceeding their costs, and, if the

project is good, the best strategy is to choose a high level of investment. Moreover, while a bad project at a low level of investment is creditworthy, implementing it at a high level of investment leads to default. We normalize the returns in that case to 0.

The entrepreneur receives a perfectly informative private signal on the project's type, and responds to it by choosing the level of investment, either L or H . Following previous studies (e.g., Manove and Padilla, 1999; Landier and Thesmar, 2008), entrepreneurs have two types of beliefs: “realistic” entrepreneurs have correct priors about the project's quality and update it using Bayes' rule, while “overconfident” entrepreneurs always believe their project is good, regardless of the signal they receive. Thus, a realistic entrepreneur chooses the high level of investment if the project is good, and the low level of investment if the project is bad. Overconfident entrepreneurs instead always choose a high investment level.

For simplicity, we assume that banks are competitive. While they do not observe the project's signal, we assume that they can observe whether borrowers are overconfident or not. This is consistent with the notion of informed lending in Inderst and Mueller (2006). The key distinction in our model is that some banks rely on collateral (“collateral-based banks”), while others do not (“non-collateral-based banks”). Under collateral-based lending, the debt contract specifies not only a promised repayment, denoted by R^{Bank} , but also the right to seize the firm's assets A in case of default.

Credit outcomes for realistic borrowers. We first characterize the credit outcomes for realistic borrowers. Because realistic borrowers choose the “right” investment level – i.e., L if the signal is bad, H if it is good – they never default ex-post. Therefore, both collateral-based and non-collateral-based banks lend to realistic borrowers, charging a repayment equal to the project's cost. Hence, realistic borrowers are always financed, invest in positive NPV projects, and never default.

Credit outcomes for overconfident borrowers. We now turn to overconfident borrowers, and show how their outcomes depend on collateral. Overconfident borrowers always choose the high investment, and thus demand financing of size H . From their viewpoint, the perceived

ex-ante profits equal: $\Pi^{\text{overconfident}} = R_{G,H} - R^{\text{Bank}}$, since they always believe the project is good. However, banks anticipate that if the project is bad, it fails at the high investment level, leading to default.

Non-collateral-based banks. Because non-collateral-based banks recoup nothing in default, their zero-profit condition for a loan of size H is:

$$(1 - \alpha)R^{\text{Bank}} = H \implies R^{\text{Bank}} = \frac{H}{1 - \alpha}$$

Plugging this expression into overconfident borrowers' perceived ex-ante profits gives $R_{G,H} - \frac{H}{1 - \alpha}$, which can be either positive or negative. When positive, i.e., when $R_{G,H} \geq \frac{H}{1 - \alpha}$, the good project return is so high that an overconfident borrower accepts the large cost of external finance, R^{Bank} , at which non-collateral-based banks break even. In this extreme case, the high return on the good project is large enough to offset the losses incurred by non-collateral-based banks when the project is bad. When $R_{G,H} < \frac{H}{1 - \alpha}$, ex-ante profits are negative, and overconfident borrowers are credit-rationed by non-collateral-based banks. We focus on this case to derive the empirical predictions below.

Collateral-based banks. Collateral-based banks seize assets A upon default. Their zero-profit condition for a loan of size H is:

$$(1 - \alpha)R^{\text{Bank}} + \alpha A = H \implies R^{\text{Bank}} = \frac{H - \alpha A}{1 - \alpha}.$$

Substituting into overconfident borrowers' perceived ex-ante profits gives:

$$\Pi^{\text{Overconfident}}(A) = R_{G,H} - \frac{H - \alpha A}{1 - \alpha}$$

which is strictly increasing in A . Hence, there exists a unique cutoff:

$$A^* \equiv \frac{H - (1 - \alpha)R_{G,H}}{\alpha}$$

such that $\Pi^{Overconfident} > 0$ if and only if $A > A^*$. Hence, collateralized lending relaxes the financing constraints of overconfident borrowers whenever their pledgeable assets exceed A^* , allowing them to finance the high-investment project. However, the true expected NPV of choosing H for an overconfident borrower is negative, and default occurs with probability α when the project is bad; in this case, collateral leads to over-borrowing.

2.2 Testable implications

Our empirical analysis focuses on three predictions about how collateral shapes borrowing, investment, and default for overconfident borrowers. While realistic borrowers are always financed, overconfident borrowers remain financially constrained unless they borrow from collateral-based banks and possess enough pledgeable assets to support collateralized lending. This mechanism is summarized in the following prediction:

Prediction 1. *Access to collateralized lending relaxes the financial constraints of overconfident borrowers.*

Realistic borrowers adjust loan size and investment to project quality, whereas overconfident borrowers always choose high investment. As a result, when collateral relaxes their financing constraints, overconfident borrowers invest more than realistic borrowers:

Prediction 2. *Collateralized lending leads overconfident borrowers to invest more than realistic borrowers.*

Realistic borrowers never default, while overconfident borrowers who receive financing default when the project turns out to be bad. Accordingly:

Prediction 3. *Collateralized lending raises ex-post default for overconfident borrowers.*

In sum, our model highlights collateral as a key mechanism through which overconfident borrowers overcome financial constraints, leading to higher investment and higher ex-post

default. Our empirical tests examine these three core outcomes—credit, investment, and ex-post default.

From model to data. In the empirical analysis, we begin by using a direct measure of a firm’s use of collateral, defined as the lagged share of its credit backed by collateral. This measure provides a first step in examining whether the collateral channel operates at the firm level—specifically, whether collateral shapes how overconfidence relates to credit and risk-taking outcomes. However, the share of collateralized credit reflects an equilibrium outcome between lenders’ preference for collateralized loans and borrowers’ availability of collateral. Since the model features both banks’ reliance on collateral and pledgeable assets, it is important to map both primitives into observables.

On the lender side, we classify banks according to their structural reliance on collateral, identifying “collateral-based” lenders as those that systematically require collateral after purging borrower composition from their loan portfolios. This classification is constructed using loan-level information from the credit register, controlling for borrower fixed effects to isolate the bank-side component of collateral requirements. Cross-bank differences in collateral usage may reflect factors such as screening technology (Ahnert et al., 2023; Core and De Marco, 2024), organizational structure, or business models emphasizing asset-backed lending.

On the borrower side, we proxy pledgeable assets, A , with asset tangibility, measured as the ratio of tangible to total assets. Tangible assets are easier to verify, value, and repossess, and are therefore more suitable as collateral for bank credit. This is a standard proxy in the corporate finance literature, where asset tangibility is widely used as an empirical measure of pledgeable capital and debt capacity (see, e.g., Rajan and Zingales, 1995; Almeida and Campello, 2007).

Taken together, these measures allow us to test the model’s predictions on credit using both lender-side and borrower-side variation in collateralized lending, and to trace their implications for investment and default. We next describe the data and empirical strategy used to test these predictions.

3 Data

We draw on several data sources to study how borrowers’ overconfidence shapes credit outcomes. Our empirical analysis relies on data from the Italian Credit Register, the Survey on Industrial and Service Firms, and the Italian Ministry of Education, which we describe in detail below. The sample period spans 2005–2017. Summary statistics are in Table 1.

[INSERT TABLE 1 HERE]

3.1 Credit register

We use detailed data from the Italian Credit Register (CR), maintained by the Bank of Italy. The CR tracks the amount of credit between each bank and firm for credit exposures over €75,000 for three categories: overdraft (i.e., unsecured, uncommitted, revolving credit lines), credit lines backed by trade receivables, and term loans. In our sample, overdraft loans account for an average of 23% of total credit granted at the bank-firm level, credit lines backed by trade receivables for 42%, and term loans for 35%.

For each loan, the CR includes information on the amount of credit backed by real collateral, at the bank-firm level.⁴ The CR does not contain information on the exact nature of the real collateral, so that we cannot distinguish whether this consists, for instance, of buildings or equipment. The reported value as collateral is the minimum between the value of the loan and of the appraisal. The appraisal value is assessed by the bank valuation expert and it is linked to the market value of the property at the time of the loan origination. In practice, only term loans are backed by real collateral, which is why we focus on this type of loans to construct the measure of collateralized lending and collateral-based banks.⁵

We observe data on interest rates for a subgroup of around 90 banks accounting for more than 80% of aggregate credit in a subsection of the CR (“Taxia”). Interest rates are calculated

⁴The CR shows the minimum between the value of the guarantee and the outstanding loan amount. This implies that for all loans that are overcollateralized we observe a 100% collateralization rate.

⁵For credit lines backed by account receivables, we do not observe the value of the guarantee, meaning there is no variation in collateralization rates that we can exploit.

as the ratio of interest payments made by the firm to the bank to the average amount of the credit used and are available for each type of loan. Moreover, banks must report to the CR when they classify a loan as “bad debt”, meaning that the borrower is insolvent or in a substantially similar situation.⁶ We measure default as a dummy equal to one if the firm’s credit exposure in year $t + 1$ is classified as bad debt by the bank.

3.2 Survey on industrial and service firms

The Survey on industrial and service firms (INVIND) is conducted annually by the Bank of Italy between February and April. It collects forecasts from firm managers on sales, investment, and employment for the upcoming year (i.e., by the end of the current fiscal year in December). We link firms in INVIND to the demographic characteristics of their top-level managers using data from the Italian Chamber of Commerce (Infocamere). These data are available from 2005 and provide the personal tax identifier of managers. We restrict our sample to senior level managers, such as the CEO, CFO, or director of sales, who are the survey respondents. From the managers’ tax identifier, we can identify the province where the managers were born, as well as their age and gender.⁷ The answers in INVIND are confidential and are released to the public only in aggregate form for statistical purposes (Guiso and Parigi, 1999). Access to this confidential data reduces concerns that managers might strategically over-report future sales, a common issue in earnings guidance data (Cain et al., 2007).

⁶Bad debt represents the final stage of a non-performing loan (NPL). NPLs are defined as the sum of bad loans and two other subcategories: past-due (late payments above 90 days) and sub-standard or unlikely-to-pay (i.e. those exposures that the bank thinks are unlikely to be paid back in full).

⁷We restrict the sample to firms with non-missing data for at least three consecutive years. Survey respondents are typically the Chief Financial Officer (CFO), the Chief Executive Officer (CEO) or other senior financial officers (firms in the survey have a minimum of 20 and a maximum of 153,000 employees).

3.3 Italian Ministry of Education (INVALSI)

We use data from the Italian National Institute for the Evaluation of the Education System (INVALSI), which administers the national standardized test for attainment evaluation introduced in 2009 to evaluate the performance of Italian schools. This test is compulsory for all primary school students (ages 9-11). Our dataset includes individual student responses from three waves (2009–2010, 2011–2012, and 2012–2013), along with information on the province in which each school is located. Importantly for our purposes, the INVALSI questionnaire asks students to report their perceived mathematical ability relative to their classmates. We aggregate these responses at the province level to construct our measure of pupils’ overconfidence, as described in more detail in Section 4.2.

4 Measuring Overconfidence and Identification

4.1 Managerial overconfidence: Firm forecast errors

There are two common ways to measure managerial overconfidence in the literature: late option-exercise (Malmendier and Tate, 2005) or positive forecast errors from firm-level surveys or earnings forecasts (Landier and Thesmar, 2008; Otto, 2014). While the former is only available for publicly listed firms, the latter can also be computed for private firms, such as those in our sample. We follow the literature on managers’ expectations data (Landier and Thesmar, 2008; Ben-David et al., 2013; Otto, 2014) and use forecasts that exceed ex-post realized outcomes as a measure of managers’ overconfidence. In particular, we compute the sales growth forecast error as the difference between the firm’s subjective forecast $F_t(\cdot)$ and future realized sales over current sales: $FE_{t+1|t} = (F_t(Sales_{t+1}) - Sales_{t+1})/Sales_t$. To measure future and current realized sales we use data from the official company accounts (Cerved), which include all Italian limited liability companies.

In Panel A of Table 1, we show that on average managers predict sales growth to be only 1.4 percentage points higher than their actual realization. However, a significant fraction

(22%) make large, positive forecast errors in excess of 10 percentage points. These forecast errors are persistent over time (Ma et al., 2019). As shown in Fig. A.1 in the Online Appendix, firms whose managers make large positive forecast errors are also more likely to default than others. This supports the idea that overconfident managers tend to be ex-post riskier. However, unexpected negative shocks could also explain the correlation between forecast errors and default. In what follows, we propose an identification strategy that relies on a measure of overconfidence which is plausibly uncorrelated with economic shocks.

4.2 Our measure: Pupils’ overconfidence

We construct a plausibly exogenous measure of overconfidence using differences across Italian provinces in pupils’ self-declared ability in mathematics relative to their classmates, based on the INVALSI data.⁸ Specifically, we define overconfidence as the fraction of pupils in a province who answer “no” to question 15.B: “Mathematics is harder for me than for many of my classmates” (see Fig. A.2 in the Online Appendix). This measure is based on research in psychology showing that students systematically overestimate their exam performance (e.g., Hacker et al., 2000). Consistent with the “better-than-average” effect, 72% of Italian students are overconfident in their mathematical ability, with significant variation across provinces.⁹ The proportion of overconfident students is correlated across the different waves of the survey, consistent with the idea that our measure reflects a persistent cultural trait.¹⁰

This particular question, unlike others in the INVALSI survey, allows us to isolate overconfidence – the tendency of pupils to overestimate their own ability relative to their peers

⁸Puri and Robinson (2007) propose a similar strategy, using health rather than education outcomes. They compare self-assessed life expectancy to that implied by statistical tables, and use the difference between the two to study the effects of optimism on households’ financial choices.

⁹Students who find mathematics equally easy and answer “no” may inflate the level of overconfidence in a given province. This is not a threat to our empirical strategy, as long as such students are evenly distributed across provinces. Similarly, even though girls exhibit lower self-confidence in mathematics (Carlana, 2019), this is not a concern for our strategy since the sex ratio is balanced across provinces. In our data, while boys are, on average, more overconfident than girls (76% vs. 68% report finding mathematics easier than their classmates), boys’ and girls’ overconfidence levels are highly correlated across provinces ($\hat{\beta} = 1.15$ and an $R^2 = 0.69$ in our data). We show below that our results are robust to using boys’ overconfidence only.

¹⁰A regression across the 110 provinces of the share of pupils who found mathematics easier than their classmates in the 2012-2013 INVALSI wave on the same variable from 2009-2010 yields $\hat{\beta} = 0.71$ and $R^2 = 0.63$.

– from other confounding factors like local differences in grading standards. For instance, in southern Italy, where “grade inflation” is more common, perceptions of what constitutes a good grade in mathematics may be skewed.¹¹

We hypothesize that pupils’ overconfidence in mathematics will also reflect the intrinsic overconfidence of local managers. In support of this hypothesis, we document a robust and significant relationship between local pupils’ overconfidence and the likelihood that local managers make large positive forecast errors about their future sales growth. As shown in Fig. 1, pupils’ overconfidence in mathematics is positively correlated with the share of local managers who make forecast errors on their future sales in excess of 10 percentage points across Italian provinces.

[INSERT FIGURE 1 HERE]

In what follows, we outline our identification strategy for estimating the effect of overconfidence on credit outcomes. Importantly, we do not aim to identify the primitive determinants of the cross-province differences in pupils’ overconfidence that we exploit. These differences likely reflect a combination of family background, peer environments, and broader local culture. For our purposes, it is sufficient that the INVALSI-based measure captures persistent variation in overconfidence that is informative about managerial beliefs later in life. As we show below, this interpretation is supported by the fact that the measure predicts managerial forecast errors, is unrelated to forecast precision, and is not systematically accounted for by a wide range of local observables once broad macro-area differences are absorbed.

4.3 Identification strategy

In order to isolate the impact of borrowers’ overconfidence on credit outcomes, we use a plausibly exogenous measure of overconfidence based on differences across Italian provinces in

¹¹For example, responses to question 15.A, “I am good at Mathematics,” might be influenced by local variations in average grades, as students of similar ability receive different grades based on their local teachers’ grading leniency. In contrast, asking whether “Mathematics is harder for me than for many of my classmates” focuses on the student’s relative ranking within the class, independent of overall grade levels.

pupils’ self-declared ability in mathematics relative to their classmates. A potential concern is that other unobserved local factors might be correlated with pupils’ overconfidence in mathematics. To address this, we exploit the presence of “movers”, i.e., managers of firms located in a different province from the one they were born in, as in Guiso et al. (2004, 2021). To the extent that overconfidence has a persistent component, whether because it is partly inherited or because expectations are shaped by past experiences (Malmendier and Nagel, 2011), overconfidence in the manager’s province of birth provides a source of variation that is distinct from contemporaneous conditions in the province where the firm currently operates. This allows us to identify the effect of overconfidence on credit outcomes within a given province, independently of confounding local shocks in the firm’s current location.¹²

We obtain managers’ province of birth from their social security number available from the Italian Chamber of Commerce. We restrict the sample to firms whose top managers were born in a different province from the one where the firm’s headquarters is located.¹³ Focusing on movers allows us to include province-year fixed effects, absorbing any other unobserved, potentially time-varying, local factors.¹⁴ Formally, we run the following regression at the firm-year level:

$$Y_{f,p,o,j,t} = \beta \text{Overconfidence}_{\text{Math},o} + \gamma'_o X_o + \gamma'_f X_{f,t-1} + \lambda_{p,t} + \lambda_{j,t} + \epsilon_{f,p,o,j,t} \quad (1)$$

where $Y_{f,p,o,j,t}$ denotes the credit outcome (the logarithm of total credit, loan rate, or the share of collateralized credit) of firm f , located in province p , run by manager born in province o , operating in sector j , in year t . $\text{Overconfidence}_{\text{Math},o}$ is the share of overconfident pupils in

¹²This is in line with a large literature focusing on the role of historical or cultural factors, such as ethnicity, customs, and oral traditions, in affecting current beliefs (Michalopoulos and Xue, 2021). For example, Guiso et al. (2016) find that self-governed Italian cities in the Middle Ages have higher levels of self-efficacy. D’Acunto et al. (2019) show that trust in finance is lower in German counties where historical antisemitism was higher at the beginning of the 20th century.

¹³When a firm has more than one manager who moved from their province of birth (15% of the observations), we take an average of the mover’s overconfidence in the province of birth of all the movers, up to four managers.

¹⁴Since firms typically borrow from banks located near their headquarters (Degryse and Ongena, 2005), the inclusion of province-year fixed effects holds the local banking market constant and isolates the effect of borrowers’ overconfidence from bank overconfidence.

province o where the firm manager was born which is different from province p where the firm is located. We control for a wide array of manager characteristics X_o , such as the risk and social preference variables from Falk et al. (2018) for the region of origin of the manager, as well as managers' age and gender. $X_{f,t-1}$ is a vector of firm characteristics (current and past growth rate of sales, sales growth volatility in the past three years, lagged leverage, EBITDA/assets, the log of firm age and total assets, the Altman credit score, age terciles and firm asset quintiles). Crucially, we include province-year fixed effects $\lambda_{p,t}$ that account for time-varying shocks across different provinces. We also include 2-digit industry-year fixed effects, $\lambda_{j,t}$, to account for time-varying shocks across sectors. Finally, standard errors are clustered at the province level to account for serial correlation of the error term within provinces.

The key identifying assumption in Eq. (1) is that, conditional on controls, pupils' overconfidence in the province where the manager is born is orthogonal to the error term. Table 2 provides results that support this claim. In Panel A, we show that other risk and social preferences at the regional level¹⁵ from Falk et al. (2018) are not correlated with pupils' overconfidence, other than a weakly significant negative correlation with trust, which is actually fully captured by the South dummy. At the more granular province level (110 provinces), we can control for local economic development using (the log of) GDP per capita; for the inefficiency of law enforcement using the average number of days it takes to complete bankruptcy proceedings in the local courts; for education using the share of the population with college degrees, and for social capital using the measure from Guiso et al. (2004), i.e., voter turnout for 92 provinces in the Italian referenda between 1946 and 1989. Panel B of Table 2 shows that pupils in the South are generally more overconfident in their mathematical ability than their fellow students in the Center who in turn are more overconfident than those in the North. Because of this underlying correlation, pupils' overconfidence is also

¹⁵Italian regions are groups of contiguous provinces. There are 20 regions, but a small one (Aosta Valley) is missing in the Falk et al. (2018) data. Given the already small sample size, we assign the social preference values of the neighboring region of Piedmont to Aosta Valley so as not to lose any observations. Excluding Aosta Valley from the sample does not affect the results.

higher in poorer areas with worse legal enforcement and lower levels of trust. Importantly, however, once we control for the North and South macro-areas, pupils’ overconfidence does not correlate with local economic development or the quality and trust in local institutions.

[INSERT TABLE 2 HERE]

Fig. 2 presents the residuals of pupils’ overconfidence after we control for the local geographic factors that we also include in Eq. (1). This is the variation in pupils’ overconfidence, net of local socioeconomic factors, that we exploit in our regressions. Overall, we conclude that, while local overconfidence is not orthogonal to local socioeconomic characteristics, the residual variation after controlling for these factors, in particular the macro-area dummies, is plausibly exogenous.

[INSERT FIGURE 2 HERE]

Finally, we acknowledge that moving is not random. Specifically, a concern is that overconfident managers might move to areas with a similar level of overconfidence. If that were the case, our estimates in the movers’ sample may still reflect confounding factors correlated with overconfidence in the area where the firm is located, rather than isolate the impact of managers’ overconfidence inherited from their place of origin. To address this concern, we construct a transition matrix for movers, breaking down the overconfidence of the place of origin and firm location in quartiles.¹⁶ The results are shown in Table A.1 in the Online Appendix. Reassuringly, we find that managers born in provinces with either low or high overconfidence are almost equally likely to move to provinces with low or high overconfidence. This test indicates that the movers’ sample can effectively separate the impact of overconfidence on credit outcomes from the confounding effects of unobserved local factors in the firm’s location.¹⁷

¹⁶To control for the fact that some migration may be due to other social and economic factors, we use the overconfidence residuals as in Fig. 2. For example, most firms with movers (75%) are located in the North of the country, consistent with the fact that internal migration is mostly from South to North.

¹⁷A related concern is whether overconfident managers match with ex-ante riskier firms, in which case it

5 Overconfidence, Credit Outcomes, and Collateral

5.1 Pupils’ overconfidence and firm forecast errors

We begin by estimating the relationship between pupils’ overconfidence and managers’ overconfidence. The results are presented in Table 3.

[INSERT TABLE 3 HERE]

In column (1), we control for firm and manager characteristics, local geographic factors, and macro-area (i.e., South and North)-year fixed effects. We find a statistically significant relationship between pupils’ overconfidence and firms’ forecast errors on their future sales. The coefficient remains stable when we include province-year fixed effects in column (2), along with industry-year and credit score-year fixed effects in column (3). Quantitatively, the effects are large: a borrower born in a province with the highest level of overconfidence is 8 percentage points more likely to make a large positive forecast error compared to a borrower from the province with the lowest level of overconfidence (0.76×0.11 , using the estimate from column 3). This represents a 36% ($0.08/0.22$) increase relative to the mean.

In columns (4)-(6), we show that the results are robust to directly regressing the forecast errors on overconfidence, rather than a dummy for a large positive forecast error. In addition, we replicate in Online Appendix Table A.3 the regressions of Table 3 using boys’ overconfidence only and find that it also strongly predicts managers’ forecast errors. Overall, these results confirm that there is a robust relationship between pupils’ and borrowers’ overconfidence across provinces.

Finally, we perform additional robustness tests that allow us to separate overplacement (Malmendier and Tate, 2005) from miscalibration (Ben-David et al., 2013) in our measure of

would not be feasible to separate overconfidence from the confounding effect of other measures of firm risk. We address this concern in two complementary ways. First, we control in our regressions for risk as well as possible with a large set of firm time-varying controls. Second, we test this hypothesis directly and present the results in Table A.2 in the Online Appendix. We do not find that overconfident managers who move join ex-ante riskier firms compared to movers from low overconfidence provinces. In the years before the overconfident managers move, the firms do not have a worse credit score, higher volatility of sales or lower profits than firms that hire managers born in less overconfident provinces.

overconfidence. We regress pupils’ overconfidence on managers’ forecast precision, as measured by the difference between the upper and lower bounds of sales forecasts, which a subset of firms report in INVIND. The results, presented in Table A.4 in the Online Appendix, indicate that we cannot reject the null hypothesis of no correlation between these two variables. This test rules out that overconfident borrowers have excessively narrow confidence intervals (i.e., that they are miscalibrated).

5.2 Credit outcomes

We next examine the effects of overconfidence on credit outcomes using Eq. (1). The results are in Table 4.¹⁸

[INSERT TABLE 4 HERE]

Panel A shows that overconfident borrowers receive smaller loans than otherwise similar borrowers. The results do not capture a “South” effect, as we control for South-year (and North-year) fixed effects. The coefficient is reduced by about half when we include province-year fixed effects in column (2), but it is still negative and statistically significant. In the most conservative specification presented in column (3), including industry-year and credit-score-year fixed effects, moving from the lowest to the highest level of borrowers’ overconfidence decreases loan amounts by 6.6% (0.11×0.6).

In Panel B, we find that borrower overconfidence is priced in loan terms. The coefficient is positive and statistically significant in each specification. Using the estimate in column (3), moving from the lowest to the highest level of borrowers’ overconfidence is associated with an increase in average loan rates by about 40 basis points (0.11×3.6), which is a 9% increase relative to the mean loan rate in the sample ($0.4/4.5$).¹⁹ In Panel C, we find that borrower overconfidence is associated with a higher share of collateralized loans, with statistically

¹⁸The results on credit outcomes are similar if we use forecast errors to measure overconfidence in the INVIND sample (Table A.5 in the Online Appendix).

¹⁹Table A.6 in the Online Appendix provides the results for different loan categories.

significant coefficients across all specifications. Using column (3), moving from the lowest to the highest level of overconfidence is associated with an increase in the share of collateralized term credit by approximately 4.6 percentage points (0.11×0.4), or about 17% relative to the sample average ($0.046/0.273$).

These results are consistent with our model in which sophisticated banks are able to observe borrowers' overconfidence and price it into their loan terms. Overall, the evidence suggests that overconfident borrowers face tighter credit restrictions both in terms of credit amounts and interest rates, and are more likely to rely on collateralized credit.

5.3 Overconfidence and collateral

In this section, we examine the role of collateral in mitigating credit constraints faced by overconfident borrowers, as predicted by the model in Section 2. To do so, we augment the specifications in Eq. (1) by including an interaction between Overconfidence and $\text{ShareColl}_{f,t-1}$, the lagged share of term loans backed by collateral at the firm-year level, scaled by its standard deviation to ease interpretation of the estimated magnitudes.²⁰ Specifically, we estimate the following regression:

$$Y_{f,p,o,j,t} = \beta_1 \text{Overconfidence}_{\text{Math},o} + \beta_2 \text{Overconfidence}_{\text{Math},o} \times \text{ShareColl}_{f,t-1} + \beta_3 \text{ShareColl}_{f,t-1} + \gamma'_o X_o + \gamma'_f X_{f,t-1} + \lambda_{p,t} + \lambda_{j,t} + \epsilon_{f,p,o,j,t} \quad (2)$$

The results are reported in Table 5. The coefficient on the (non-interacted) Overconfidence variable is negative and statistically significant, consistent with the evidence above that overconfident borrowers obtain smaller credit amounts. Using the estimate in column (3), moving from the lowest to the highest level of borrower overconfidence is associated with an 8.1% decline in loan amounts in the absence of collateral (0.11×0.74). In contrast, the interaction between overconfidence and the share of collateralized loans is positive

²⁰We focus on term loans, as collateral values are observable only for this loan type, as discussed in Section 3.1.

and statistically significant in every specification. This implies that collateral attenuates the reduction in credit associated with overconfidence: as a larger share of borrowing is collateralized, the difference in credit volumes between low- and high-overconfidence borrowers becomes smaller, and overconfident borrowers can borrow more than they otherwise would. The implied effect is economically meaningful. In column (3), a one-standard-deviation increase in the share of collateralized credit reduces the credit-volume gap associated with moving from the lowest to the highest overconfidence level by about 45% (0.33/0.74).²¹

[INSERT TABLE 5 HERE]

5.3.1 Measuring collateral: Collateral-based banks

A concern with the analysis presented in Table 5 is that the share of collateralized credit may be endogenous to unobserved firm characteristics. For instance, overconfident borrowers may be more inclined to invest in assets that can serve as collateral, thereby increasing their access to credit. To partially mitigate this concern, we instrument the share of collateralized credit using the supply-side reliance on collateral by the firm’s relationship banks. To measure differences in banks’ reliance on collateral, we run the following regression at the bank-firm-year level:

$$\text{ShareColl}_{f,b,t} = \text{BankColl}_{b,t} + \text{FirmColl}_{f,t} + \epsilon_{f,b,t}, \quad (3)$$

where $\text{ShareColl}_{f,b,t}$ is the share of collateralized term credit between firm f and bank b in year t . We include $\text{BankColl}_{b,t}$ (bank-year fixed effects) and $\text{FirmColl}_{f,t}$ (firm-year fixed effects). We interpret the estimated $\text{BankColl}_{b,t}$ as capturing each bank’s “reliance on collateral,” net of firm-specific demand for collateralized loans.

We examine the properties of the estimated $\text{BankColl}_{b,t}$ and its relationship with a range of bank characteristics; the results are reported in Online Appendix Table A.7. First, we find

²¹In Table A.8 in the Online Appendix we re-estimate the most saturated specification from column (3) of Table 5 separately for three sub-periods: the pre-crisis period (2005-2007), the crisis period encompassing both the global financial and sovereign debt crises (2008-2012), and a post-crisis period (2013-2017). The results are qualitatively similar across sub-periods, with collateral consistently associated with a sizeable reduction in the credit-volume gap between low- and high-overconfidence borrowers.

that $\text{BankColl}_{b,t}$ is highly persistent over time with an autoregressive coefficient of 0.8. Second, $\text{BankColl}_{b,t}$ is not significantly correlated with the following observable bank characteristics: bank size, capital ratios, the share of non-performing loans, a dummy for headquarters in Southern Italy, and a dummy for cooperative banks. Overall, although we do not interpret $\text{BankColl}_{b,t}$ as exogenous to bank characteristics, it is reassuring that the measure is not strongly related to standard bank observables, as this mitigates the concern that our results below might be driven by conventional balance-sheet characteristics or broad differences in banks' business models rather than by variation in banks' reliance on collateral.

We next construct a firm-level measure of collateral reliance by taking a weighted average of the estimated bank-year fixed effects: $\text{BankColl}_{f,t} = \sum_b w_{b,f,t} \text{BankColl}_{b,t}$, where the weights $w_{b,f,t}$ represent the share of credit extended by bank b to firm f in year t . We then replace the share of collateralized term credit $\text{ShareColl}_{f,t-1}$ in Eq. (2) with $\text{BankColl}_{f,t-1}$, scaled by its standard deviation to ease interpretation of the estimated magnitudes. This variable captures the propensity of the firm's relationship banks to use collateral, independent of firm-specific borrowing behavior. The results are reported in Panel A of Table 6.

[INSERT TABLE 6 HERE]

The results corroborate those in Table 5 using $\text{ShareColl}_{f,t-1}$, both qualitatively and quantitatively. The coefficient on the (non-interacted) Overconfidence variable is negative and statistically significant, indicating that more overconfident borrowers receive smaller credit amounts. The interaction between Overconfidence and $\text{BankColl}_{f,t-1}$, our measure of the firm's relationship banks' propensity to rely on collateral, is positive and statistically significant in every specification. These results confirm that collateral mitigates the credit constraints faced by overconfident borrowers. The effect is economically meaningful: in column (3), a one-standard-deviation increase in $\text{BankColl}_{f,t-1}$ reduces the credit-volume gap between the lowest and highest overconfidence levels by about 44% ($0.246/0.562$).²²

²²This magnitude is expressed relative to the estimated change between the lowest and highest overconfidence levels for firms with $\text{BankColl}_{f,t-1} = 0$. In that case, the coefficient on the (non-interacted) Overconfidence

5.3.2 Measuring collateral: Asset tangibility

As an alternative test for the role of collateral in lending to overconfident borrowers, we exploit sectoral differences in the pledgeability of firms' assets as borrower-side variation in collateralized lending. Specifically, we run the same specifications as in Eq. (2) except that we interact the variable Overconfidence with the ratio of tangible assets (which are easier to pledge as collateral) to total assets at the 2-digit industry-year level, scaled by its standard deviation, and present the results in Table 7. The results are consistent with those in Table 5 using $\text{ShareColl}_{f,t-1}$. The coefficient on the (non-interacted) Overconfidence variable is negative and statistically significant, indicating that overconfident borrowers receive smaller credit amounts. Moreover, the interaction between Overconfidence and Asset Tangibility is positive and statistically significant in every specification. These results confirm that access to collateral, using here differences in access to pledgeable assets across industries, mitigates the credit constraints faced by overconfident borrowers. The effect is economically meaningful: in column (3), a one-standard-deviation increase in Asset Tangibility reduces the credit-volume gap between the lowest and highest overconfidence levels by about 29% ($0.335/1.152$).

5.4 Investment and default

Our findings so far have shown that banks' collateral reliance matters for the allocation of credit to overconfident borrowers. A natural follow-up question is whether credit allocation affects corporate outcomes. Since collateral relaxes the credit constraints of overconfident borrowers, access to bank credit may further exacerbate over-investment by overconfident managers, and their probability of default. In the following subsections, we provide insights on these questions.

Investment. We compute the firm-level investment rate, defined as the change in assets over total assets in the previous year. We test whether overconfident borrowers invest more

variable implies that moving from the lowest to the highest level of borrower overconfidence is associated with a 6.2% decline in loan amounts (0.11×0.562).

than other borrowers when they rely more on collateralized credit, using a specification similar to Eq. (2). The results are presented in Table 8.

[INSERT TABLE 8 HERE]

We first confirm in column (1) that corporate investment is higher for overconfident borrowers. This finding echoes previous studies showing that overconfident managers invest more than others (Malmendier and Tate, 2005; Ben-David et al., 2013). In columns (2)-(4), we add the interaction term between Overconfidence and $\text{BankColl}_{f,t-1}$ (scaled by its standard deviation). The coefficient on the interaction term is positive and statistically significant, indicating that the sensitivity of investment to borrower overconfidence increases with collateralized lending. Quantitatively, the estimate on the interaction term in column (4) indicates that a one-standard-deviation increase in $\text{BankColl}_{f,t-1}$ is associated with an increase in investment rate for the highest overconfidence levels relative to the lowest overconfidence levels by about 0.4 percentage points (0.038×0.11). This is a 7% increase compared to the average investment rate in the sample.

Default. We then explore the effect of borrower overconfidence on default and bank loan losses. To measure default, we obtain loans classified as “bad debt” by banks in the CR. The results are presented in Table 9.

[INSERT TABLE 9 HERE]

First, we investigate the effect of overconfidence on one-year default probabilities, regressing a dummy equal to one if the firm credit exposure is classified as bad debt by the bank in year $t + 1$ on our local measure of overconfidence. The estimate in column (1) indicates that firms from the most overconfident provinces have default rates that are 2.6 percentage points higher (0.24×0.11) than those from the least overconfident provinces. This is a large effect when compared to the average default rate of 2.9% in our sample.

To assess the impact of higher default rates on bank balance sheets, we have to take into account the evidence from Table 4 where we show that overconfident borrowers pay higher

rates. Given that the average recovery rate on bad loans to non-financial firms is around 36%, a simple calculation suggests that loan rates should be around 1.7 percentage points higher for borrowers from the most overconfident provinces in order to compensate banks for the additional default risk they bear. We compute this number as the additional default rate for overconfident borrowers estimated in column (1) of Table 9 times the effect of moving from the least to the most overconfident province, times the loss-given-default ($0.24 \times 0.11 \times 0.64$). The estimates on loan rates in Table 4 imply that the interest rate charged to the most overconfident borrowers is on average 0.4 (0.036×0.11) to 0.68 (0.062×0.11) percentage points higher than the one charged to the least overconfident borrowers. This suggests that loan pricing only partially offsets the additional default risk banks incur when lending to overconfident borrowers.

Second, we examine whether our estimates are quantitatively large enough to explain the distribution of bad loans in the cross-section of provinces and banks. We aggregate the amount of bad loans at the province or bank-province level and look at whether collateral-based banks have a higher volume of bad loans when lending to overconfident borrowers. We confirm in Table 9 columns (2)-(7) that default rates are higher in overconfident provinces and that the higher incidence of aggregate default is driven by collateral-based banks.

Finally, we use these estimates to compute a back-of-the-envelope estimate of the aggregate amount of overconfidence-induced default that could have been avoided if banks had relied less on collateralized lending. To do so, we use the group of borrowers with the lowest level of overconfidence ($\text{Overconfidence}_{\text{Math,p}} = 0.677$, see summary statistics) and the group of banks with low reliance on collateral ($\text{HighBankColl} = 0$) as a counterfactual. We compute it using the following expression:

$$\Delta \text{BadLoans} = \sum_{b \in \text{HighBankColl}=1} \sum_p \beta \times (\text{Overconfidence}_{\text{Math,p}} - 0.677) \times \text{Credit}_b.$$

where $\beta = 0.008$ is the estimate on the interaction term $\text{Overconfidence}_{\text{Math,p}} \times \text{HighBankColl}_b$

in column (7) of Table 9, and Credit_b is total loan portfolio size in euros of bank b . For 2017 (the last year of our sample), we find that collateralized lending led to an increase in overconfidence-induced bad loans of around €6.7 billion. This represents 6% of the aggregate stock of bad loans for non-financial corporate lending in Italy in 2017. Note that even if banks ask for more collateral and higher rates when lending to overconfident borrowers, recovery rates on bad loans are quite low, even when they are secured by collateral: on average, only 36% of the loans to non-financial firms are recovered when the loan is classified as bad debt. This suggests that the collateral channel matters quantitatively for understanding the real effects of borrower overconfidence on banks' balance sheets in the aggregate.

6 Conclusion

We study how overconfident borrowers interact with banks in credit markets. Since overconfidence is endogenous, our identification strategy relies on variation in pupils' overconfidence across provinces in Italy from the national education test. Pupils' overconfidence predicts the likelihood that local managers issue over-optimistic sales growth forecasts. To strengthen identification, we leverage a movers' design, exploiting variation in managers' province of birth to isolate the effect of overconfidence from local economic conditions.

Our main contribution is to show that the interaction between borrower overconfidence and banks' reliance on collateral plays a central role in shaping credit outcomes. Importantly, the collateral lending channel amplifies the real effects associated with overconfidence: overconfident borrowers receive more credit and invest more when they borrow from collateral-based banks. In turn, overconfident borrowers default more frequently ex-post, with aggregate implications for the distribution of non-performing loans in the cross-section of provinces and banks. Overall, our findings provide new insights into the interplay between biased expectations and bank lending practices, offering important implications for understanding the aggregate economic impact of managers' overconfidence.

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Figure 1: **Probability of Issuing Overconfident Forecast**

This figure reports a scatter plot of firms' likelihood of issuing overconfident forecasts at the province level, i.e., the province-average of $\mathbb{1}(FE_{t+1|t} > 0.1)$, on pupils' overconfidence in mathematics.

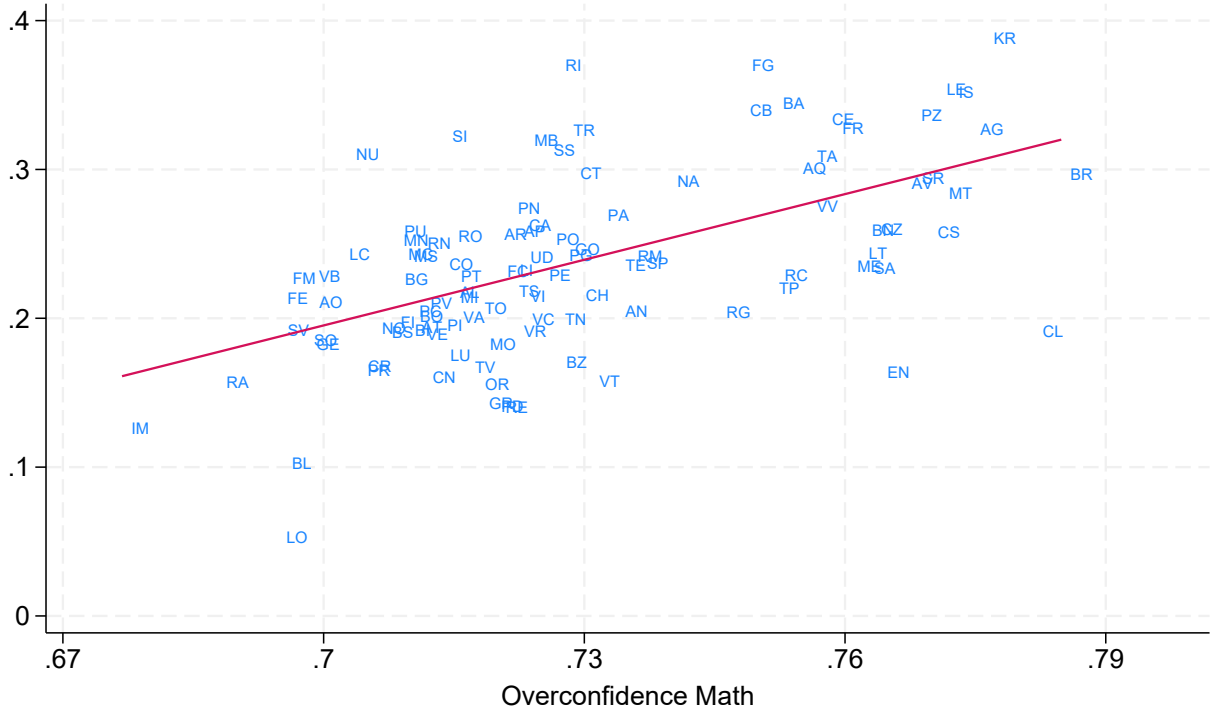


Figure 2: **Overconfidence in Mathematics**

This map reports the residuals from a regression of pupils' overconfidence, i.e. the share of pupils who find mathematics easier than their classmates for each Italian province averaged between 2009 and 2013, on local geographic controls. Geographic controls include: the log of average GDP per capita, the length of bankruptcy proceedings, the region-averages from the preference survey in Falk et al. (2018), and a dummy for the South.

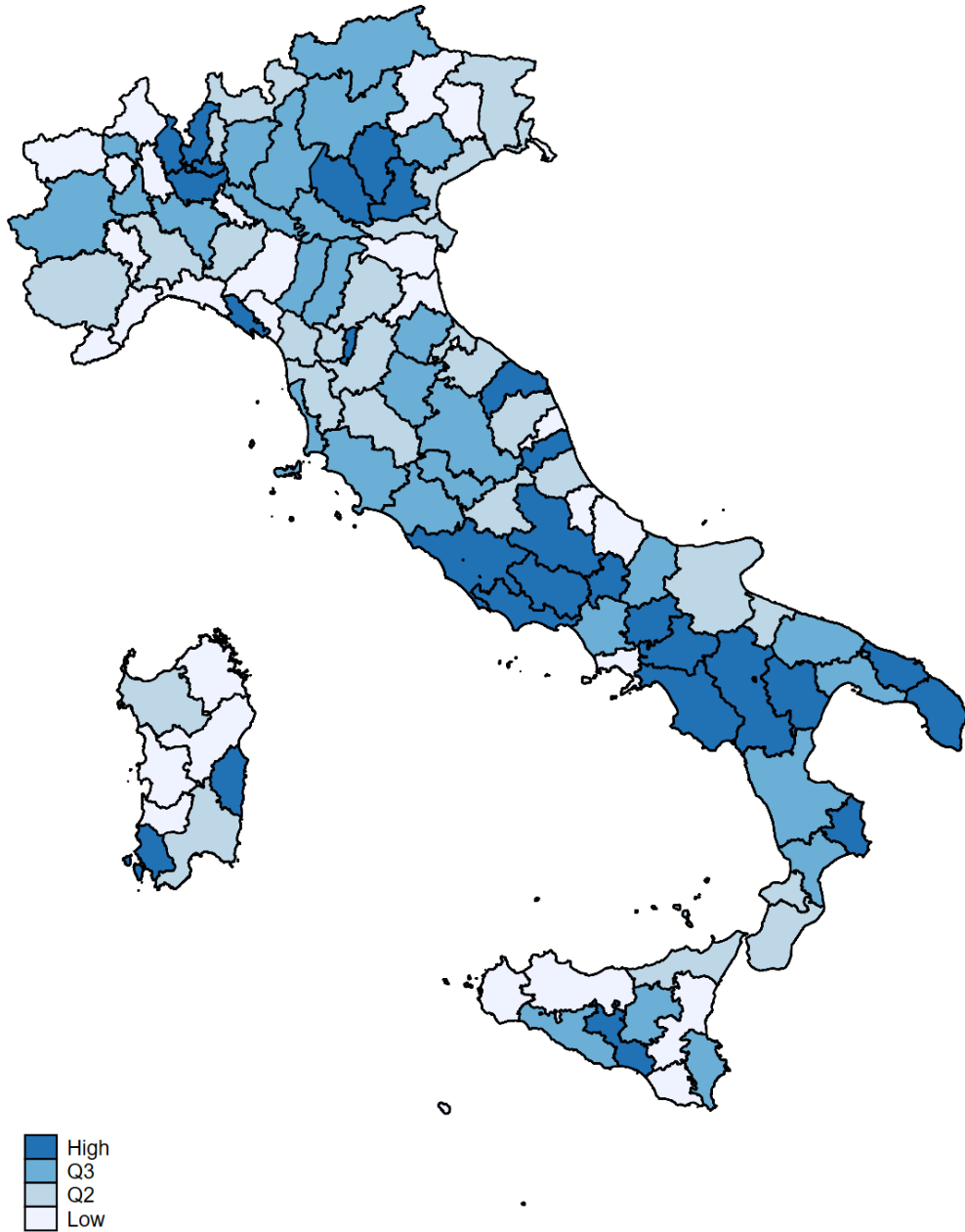


Table 1: Summary Statistics

This table presents the summary statistics for our data at the firm-year level (2005-2017) for the INVIND sample, which consists of about 2,000 firms (Panel A); at the province level from INVALSI and other province characteristics such as GDP per capita; Law Inefficiency (i.e., the average length of bankruptcy proceedings from local courts in days) and regional level risk, time and social preferences from Falk et al. (2018) survey (Panel B); the full CR sample in 2005-2017 at the firm level (Panel C); and bank-year characteristics (Panel D). All firm-year and firm-bank-year variables have been winsorized at the 1st-99th percentiles.

	(1)	(2)	(3)	(4)	(5)	(6)
	Obs.	Mean	SD	P1	P50	P99
Panel A. INVIND Survey, firm-year level						
$FE_{t+1 t} = \frac{F_t(Sales_{t+1}) - Sales_{t+1}}{Sales_t}$	11726	0.014	0.180	-0.608	0.010	0.662
$\mathbb{1}(FE_{t+1 t} > 0.1)$	11726	0.223	0.419	0	0	1
Interval Forecast Sales Growth (Max-Min) $_{t+1 t}$	3849	0.081	0.078	0	0.06	0.428
Sales Growth (t,t+1)	11726	0.022	0.200	-0.580	0.017	0.785
Sales Growth Volatility	11726	0.156	0.168	0.008	0.104	1.000
Firm Age (years)	11726	29.321	17.885	4	26	90
Firm Assets (€million)	11726	90.859	235.530	1.537	28.331	1175.377
Leverage	11726	0.350	0.162	0.069	0.331	0.867
EBITDA/Assets	11726	0.078	0.083	-0.177	0.072	0.346
Credit Score	11726	4.310	1.860	1	4	9
Panel B. INVALSI, province or region characteristics						
Overconfidence	110	0.727	0.025	0.677	0.722	0.782
GDP/Pop (€)	110	21478	5724	12679	21521	34776
Law Inefficiency (days)	110	4129	2080	1259	3690	11558
Patience	20	0.103	0.184	-0.350	0.109	0.514
Risk Taking	20	-0.110	0.155	-0.379	-0.123	0.245
Positive Reciprocity	20	0.175	0.222	-0.102	0.191	0.789
Negative Reciprocity	20	0.305	0.285	-0.399	0.369	0.810
Altruism	20	0.346	0.227	-0.047	0.281	0.825
Trust	20	-0.091	0.162	-0.545	-0.082	0.154
Panel C. Borrower Characteristics, firm-year level						
Log(Credit)	457649	13.616	1.509	11.284	13.450	17.274
Loan Rate (%)	457649	4.524	2.778	0	4.579	10.834
ShareColl $_{ft}$	400677	0.273	0.387	0	0	1
BankColl $_{f,t-1}$	380715	-0.001	0.044	-0.127	0.000	0.124
AssetTangibility	457862	0.230	0.137	0.077	0.169	0.695
Investment Rate	380765	0.062	0.261	-0.486	0.015	1.226
Default Rate	432655	0.029	0.167	0.000	0.000	1.000
Sales Growth (t,t+1)	457862	0.111	0.737	-0.816	0.016	3.352
Sales Growth Volatility	457862	0.403	0.759	0.010	0.178	4.496
Firm Age (years)	457862	14.411	1.984	4	15	60
Firm Assets (€million)	457862	2.049	0.004	0.147	1.682	158.736
Leverage	457862	0.739	0.265	0.180	0.781	1.092
EBITDA/Assets	457862	0.082	0.127	-0.239	0.074	0.415
Credit Score	457862	5.178	2.041	1	5	9
Panel D. Bank Characteristics, bank-year level						
BankColl $_{bt}$	3521	-0.0003	0.152	-0.625	-0.057	0.746
CapRatio $_{bt-1}$	3521	10.81	3.00	1.03	10.32	32.60
NPL/Assets $_{bt-1}$	3521	3.88	3.64	0.00	2.69	30.30
Log(Assets) $_{bt-1}$	3521	6.76	1.48	3.65	6.46	13.83
Cooperative Bank	3521	0.76	0.43	0.00	1.00	1.00
HQ South	3521	0.18	0.39	0.00	0.00	1.00

Table 2: **Overconfidence and Other Local Characteristics**

In Panel A, the unit of observation is a region. The dependent variable is the share of pupils at the regional level who say they find mathematics easier than their classmates. Local preferences in the region are obtained from Falk et al. (2018) and are: Patience, Risk Taking, Positive Reciprocity, Negative Reciprocity, Altruism, and Trust. In Panel B, the unit of observation is a province. The dependent variable is the share of pupils at the province level who say they find mathematics easier than their classmates. South (North) is a dummy equal to one for provinces located in the south (north) of Italy (the center represents the omitted category); Log(GDP/Pop) is the log of average GDP per capita; Law Inefficiency is the log of the average number of days it takes to complete bankruptcy proceedings in the local courts; Share College is the share of population with a college degree from the 2011 ISTAT Census; Social Capital is the measure of social capital from Guiso et al. (2004), i.e. the average voter turnout in Italian referenda at the province level between 1946 and 1989 (available for 92 provinces). Standard errors presented in parentheses are heteroskedasticity-robust. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. Region-level Overconfidence								
South								0.030*** (0.007)
Patience	-0.005 (0.030)						0.000 (0.048)	-0.018 (0.031)
Risk Taking		0.017 (0.035)					0.031 (0.043)	0.028 (0.027)
Positive Reciprocity			0.024 (0.024)				0.052 (0.037)	0.033 (0.023)
Negative Reciprocity				-0.005 (0.019)			-0.041 (0.031)	-0.022 (0.020)
Altruism					-0.009 (0.024)		-0.017 (0.037)	-0.012 (0.023)
Trust						-0.058* (0.031)	-0.092* (0.047)	-0.053 (0.031)
Observations	20	20	20	20	20	20	20	20
R ²	0.002	0.013	0.052	0.003	0.008	0.162	0.442	0.796
Panel B. Province-level Overconfidence								
	(1)	(2)	(3)	(4)	(5)	(6)		
South	0.027*** (0.005)						0.010 (0.010)	
North	-0.011*** (0.004)						-0.007 (0.005)	
Log(GDP/Pop)		-0.060*** (0.008)					-0.021 (0.014)	
Law Inefficiency			0.029*** (0.004)				-0.001 (0.006)	
Share College				-0.121 (0.117)			0.054 (0.106)	
Social Capital					-0.204*** (0.018)		-0.079 (0.049)	
Observations	110	110	110	110	92	92		
R ²	0.500	0.428	0.260	0.009	0.515	0.589		

Table 3: **Pupils' Overconfidence and Firm Forecast Errors**

The unit of observation is a firm-year. The dependent variable is $\mathbb{1}(FE_{t+1|t} > 0.1)$ in columns (1)-(3), a dummy equal to one if the firm forecast error on future sales growth exceeds 10 percentage points, 0 otherwise, and the firm forecast error on future sales ($FE_{t+1|t}$) in columns (4)-(6). Overconfidence is the share of pupils who say that they find mathematics easier than their classmates in the province where the manager is born. Firm controls include current realized and past sales growth, sales growth volatility over the past three years, lagged leverage, lagged EBITDA/assets, the log of firm age and firm-age terciles, the log of total assets and quintiles of total assets, the Cerved Altman Z-score index, ranging from 1 (lowest risk) to 9 (highest risk). Manager controls are the same geographic controls calculated for the province or region (Falk et al., 2018) of birth of the manager, a female dummy indicator and the (log of) manager's age. Geographic controls include: region-averages from the preference risk survey in Falk et al. (2018), i.e. Patience, Risk Taking, Positive Reciprocity, Negative Reciprocity, Altruism, and Trust; the log of province-level GDP per capita in each year; the log of the province-average length of bankruptcy proceedings in days. Fixed effects include: South-Year&North-Year denotes macro-areas for north and south $\times$ year; Prov-Year denotes province $\times$ year; Industry-Year denotes 2-digit industry $\times$ year; $\mathbb{1}(\text{Credit Score})$ -Year denotes dummies for each Cerved Altman Z-score $\times$ year. Standard errors presented in parentheses are clustered at the province level. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	$\mathbb{1}(FE_{t+1 t} > 0.1)$			$FE_{t+1 t}$		
Overconfidence	0.692*** (0.255)	0.699** (0.267)	0.762*** (0.287)	0.215** (0.083)	0.253*** (0.093)	0.262** (0.108)
Firm&Manager Controls	Y	Y	Y	Y	Y	Y
Geographic Controls	Y	-	-	Y	-	-
South&North-Year FE	Y	-	-	Y	-	-
Prov-Year FE	N	Y	Y	N	Y	Y
Industry-Year FE	N	N	Y	N	N	Y
$\mathbb{1}(\text{Credit Score})$ -Year FE	N	N	Y	N	N	Y
Observations	11726	11726	11726	11726	11726	11726
R^2	0.263	0.356	0.426	0.549	0.603	0.646

Table 4: Overconfidence and Credit Outcomes

The unit of observation is a firm-year. In Panel A the dependent variable is the logarithm of total credit, in Panel B it is the average interest rate across loan types and in Panel C it is the share of collateralized term credit. Overconfidence is the share of pupils who say that they find mathematics easier than their classmates in the province where the manager is born. Firm controls include current realized and past sales growth, sales growth volatility over the past three years, lagged leverage, lagged EBITDA/assets, the log of firm age and firm-age terciles, the log of total assets and quintiles of total assets, the Cerved Altman Z-score index, ranging from 1 (lowest risk) to 9 (highest risk). Manager controls are the same geographic controls calculated for the province or region (Falk et al., 2018) of birth of the manager, a female dummy indicator and the (log of) manager's age. Geographic controls include: region-averages from the preference risk survey in Falk et al. (2018), i.e. Patience, Risk Taking, Positive Reciprocity, Negative Reciprocity, Altruism, and Trust; the log of province-level GDP per capita in each year; the log of the province-average length of bankruptcy proceedings in days. Fixed effects include: South-Year&North-Year denotes macro-areas for north and south $\times$ year; Prov-Year denotes province $\times$ year; Industry-Year denotes 2-digit industry $\times$ year; $\mathbb{1}(\text{Credit Score})$ -Year denotes dummies for each Cerved Altman Z-score $\times$ year. Standard errors presented in parentheses are clustered at the province level. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)
	Panel A. Log(Credit)		
Overconfidence	-1.109*** (0.220)	-0.499*** (0.167)	-0.612*** (0.129)
Observations	457862	457862	457649
R^2	0.735	0.738	0.754
	Panel B. Average Loan Rate (%)		
Overconfidence	6.170*** (0.868)	3.862*** (0.548)	3.641*** (0.596)
Observations	457862	457862	457649
R^2	0.184	0.203	0.237
	Panel C. Share Collateralized Credit		
Overconfidence	0.582*** (0.128)	0.694*** (0.106)	0.418*** (0.095)
Firm&Manager controls	Y	Y	Y
Geographic Controls	Y	-	-
South-Year&North-Year FE	Y	-	-
Prov-Year FE	N	Y	Y
Industry-Year FE	N	N	Y
$\mathbb{1}(\text{Credit Score})$ -Year FE	N	N	Y
Observations	400875	400875	400677
R^2	0.065	0.076	0.168

Table 5: **Overconfidence, Collateral, and Credit**

The unit of observation is a firm-year. The dependent variable is the logarithm of total credit. Overconfidence is the share of pupils who say that they find mathematics easier than their classmates in the province where the manager is born. $\text{ShareColl}_{f,t-1}$ is the firm's lagged share of collateralized term credit, scaled by its standard deviation. Firm controls include current realized and past sales growth, sales growth volatility over the past three years, lagged leverage, lagged EBITDA/assets, the log of firm age and firm-age terciles, the log of total assets and quintiles of total assets, the Cerved Altman Z-score index, ranging from 1 (lowest risk) to 9 (highest risk), and the non-interacted term $\text{ShareColl}_{f,t-1}$. Manager controls are the same geographic controls calculated for the province or region (Falk et al., 2018) of birth of the manager, a female dummy indicator and the (log of) manager's age. Geographic controls include: region-averages from the preference risk survey in Falk et al. (2018), i.e. Patience, Risk Taking, Positive Reciprocity, Negative Reciprocity, Altruism, and Trust; the log of province-level GDP per capita in each year; the log of the province-average length of bankruptcy proceedings in days. Fixed effects include: South-Year&North-Year denotes macro-areas for north and south $\times$ year; Prov-Year denotes province $\times$ year; Industry-Year denotes 2-digit industry $\times$ year; $\mathbb{1}(\text{Credit Score})$ -Year denotes dummies for each Cerved Altman Z-score $\times$ year. Standard errors presented in parentheses are clustered at the province level. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)
	Log(Credit)		
Overconfidence	-1.151*** (0.209)	-0.611*** (0.164)	-0.740*** (0.141)
Overconfidence $\times$ ShareColl $_{f,t-1}$	0.382*** (0.102)	0.383*** (0.105)	0.329*** (0.101)
Firm&Manager Controls	Y	Y	Y
Geographic Controls	Y	-	-
South-Year&North-Year FE	Y	-	-
Prov-Year FE	N	Y	Y
Industry-Year FE	N	N	Y
$\mathbb{1}(\text{Credit Score})$ -Year FE	N	N	Y
Observations	391578	391578	391388
R^2	0.756	0.759	0.776

Table 6: **Overconfidence, Bank Reliance on Collateral, and Credit**

The unit of observation is a firm-year. The dependent variable is the logarithm of total credit. Overconfidence is the share of pupils who say that they find mathematics easier than their classmates in the province where the manager is born. $\text{BankColl}_{f,t-1}$ is the lagged firm-year weighted average of the bank-year fixed effects ($\text{BankColl}_{b,t-1}$) as estimated in Eq. (3), scaled by its standard deviation. Firm controls include current realized and past sales growth, sales growth volatility over the past three years, lagged leverage, lagged EBITDA/assets, the log of firm age and firm-age terciles, the log of total assets and quintiles of total assets, the Cerved Altman Z-score index, ranging from 1 (lowest risk) to 9 (highest risk), and the non-interacted term $\text{BankColl}_{f,t-1}$. Manager controls are the same geographic controls calculated for the province or region (Falk et al., 2018) of birth of the manager, a female dummy indicator and the (log of) manager's age. Geographic controls include: region-averages from the preference risk survey in Falk et al. (2018), i.e. Patience, Risk Taking, Positive Reciprocity, Negative Reciprocity, Altruism, and Trust; the log of province-level GDP per capita in each year; the log of the province-average length of bankruptcy proceedings in days. Fixed effects include: South-Year&North-Year denotes macro-areas for north and south $\times$ year; Prov-Year denotes province $\times$ year; Industry-Year denotes 2-digit industry $\times$ year; $\mathbb{1}(\text{Credit Score})$ -Year denotes dummies for each Cerved Altman Z-score $\times$ year. Standard errors presented in parentheses are clustered at the province level. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)
	Log(Credit)		
Overconfidence	-0.974*** (0.230)	-0.334* (0.180)	-0.562*** (0.137)
Overconfidence $\times$ BankColl $_{f,t-1}$	0.302*** (0.105)	0.308*** (0.097)	0.246** (0.096)
Firm&Manager Controls	Y	Y	Y
Geographic Controls	Y	-	-
South-Year&North-Year FE	Y	-	-
Prov-Year FE	N	Y	Y
Industry-Year FE	N	N	Y
$\mathbb{1}(\text{Credit Score})$ -Year FE	N	N	Y
Observations	380715	380715	380527
R^2	0.709	0.713	0.735

Table 7: **Overconfidence, Asset Tangibility, and Credit**

The unit of observation is a firm-year. The dependent variable is the logarithm of total credit. Overconfidence is the share of pupils who say that they find mathematics easier than their classmates in the province where the manager is born. AssetTangibility is the (lagged) ratio of tangible fixed assets over total assets at the 2-digit industry-year level, scaled by its standard deviation. Firm controls include current realized and past sales growth, sales growth volatility over the past three years, lagged leverage, lagged EBITDA/assets, the log of firm age and firm-age terciles, the log of total assets and quintiles of total assets, the Cerved Altman Z-score index, ranging from 1 (lowest risk) to 9 (highest risk), and the non-interacted term Asset Tangibility. Manager controls are the same geographic controls calculated for the province or region (Falk et al., 2018) of birth of the manager, a female dummy indicator and the (log of) manager's age. Geographic controls include: region-averages from the preference risk survey in Falk et al. (2018), i.e. Patience, Risk Taking, Positive Reciprocity, Negative Reciprocity, Altruism, and Trust; the log of province-level GDP per capita in each year; the log of the province-average length of bankruptcy proceedings in days. Fixed effects include: South-Year&North-Year denotes macro-areas for north and south $\times$ year; Prov-Year denotes province $\times$ year; Industry-Year denotes 2-digit industry $\times$ year; 1(Credit Score)-Year denotes dummies for each Cerved Altman Z-score $\times$ year. Standard errors presented in parentheses are clustered at the province level. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)
	Log(Credit)		
Overconfidence	-1.457*** (0.332)	-0.832*** (0.266)	-1.152*** (0.195)
Overconfidence $\times$ AssetTangibility	0.220** (0.098)	0.243** (0.094)	0.335*** (0.088)
Firm&Manager Controls	Y	Y	Y
Geographic Controls	Y	-	-
South-Year&North-Year FE	Y	-	-
Prov-Year FE	N	Y	Y
Industry-Year FE	N	N	Y
1(Credit Score)-Year FE	N	N	Y
Observations	457862	457862	457649
R^2	0.725	0.728	0.746

Table 8: **Overconfidence, Collateral, and Investment**

The unit of observation is a firm-year. The dependent variable is the firm investment rate, i.e. the change in total assets over lagged assets. Overconfidence is the share of pupils who say that they find mathematics easier than their classmates in the province where the manager is born. $\text{BankColl}_{f,t-1}$ is the lagged firm-year weighted average of the bank-year fixed effects ($\text{BankColl}_{b,t-1}$) as estimated in Eq. (3), scaled by its standard deviation. Firm controls include current realized and past sales growth, sales growth volatility over the past three years, lagged leverage, lagged EBITDA/assets, the log of firm age and firm-age terciles, the log of total assets and quintiles of total assets, the Cerved Altman Z-score index, ranging from 1 (lowest risk) to 9 (highest risk), and in columns (2)-(4) the non-interacted term $\text{BankColl}_{f,t-1}$. Manager controls are the same geographic controls calculated for the province or region (Falk et al., 2018) of birth of the manager, a female dummy indicator and the (log of) manager's age. Geographic controls include: region-averages from the preference risk survey in Falk et al. (2018), i.e. Patience, Risk Taking, Positive Reciprocity, Negative Reciprocity, Altruism, and Trust; the log of province-level GDP per capita in each year; the log of the province-average length of bankruptcy proceedings in days. Fixed effects include: South-Year&North-Year denotes macro-areas for north and south $\times$ year; Prov-Year denotes province $\times$ year; Industry-Year denotes 2-digit industry $\times$ year; $\mathbb{1}(\text{Credit Score})$ -Year denotes dummies for each Cerved Altman Z-score $\times$ year. Standard errors presented in parentheses are clustered at the province level. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)
		Investment Rate		
Overconfidence	0.052*	0.053*	0.011	-0.001
	(0.030)	(0.030)	(0.027)	(0.027)
Overconfidence $\times$ $\text{BankColl}_{f,t-1}$		0.053**	0.062***	0.038*
		(0.022)	(0.021)	(0.021)
Firm&Manager Controls	Y	Y	Y	Y
Geographic Controls	Y	Y	-	-
South-Year&North-Year FE	Y	Y	-	-
Prov-Year FE	N	N	Y	Y
Industry-Year FE	N	N	N	Y
$\mathbb{1}(\text{Credit Score})$ -Year FE	N	N	N	Y
Observations	380765	380765	380765	380759
R ²	0.124	0.124	0.128	0.152

Table 9: **Overconfidence, Collateral, and Default**

The dependent variable is the 1-year probability of default at firm level (=1 if the loan becomes bad debt in year $t+1$) in column (1), the share of bad loans over total credit at the province (columns 2-3) or bank-province (columns 4-7) in each year. Overconfidence is the share of pupils who say that they find mathematics easier than their classmates in the province in columns (2)-(7), and in the province where the manager is born in column (1). Firm controls include current realized and past sales growth, sales growth volatility over the past three years, lagged leverage, lagged EBITDA/assets, the log of firm age and firm-age terciles, the log of total assets and quintiles of total assets, the Cerved Altman Z-score index, ranging from 1 (lowest risk) to 9 (highest risk). Manager controls are the same geographic controls calculated for the province or region (Falk et al., 2018) of birth of the manager, a female dummy indicator and the (log of) manager's age. Geographic controls include: region-averages from the preference risk survey in Falk et al. (2018), i.e. Patience, Risk Taking, Positive Reciprocity, Negative Reciprocity, Altruism, and Trust; the log of province-level GDP per capita in each year; the log of the province-average length of bankruptcy proceedings in days. HighBankColl is a dummy equal to one for banks with positive bank-year fixed effects as estimated in Eq. (3). Fixed effects include: South-Year&North-Year denotes macro-areas for north and south $\times$ year; Prov-Year denotes province $\times$ year; Industry-Year denotes 2-digit industry $\times$ year; $\mathbb{1}(\text{Credit Score})$ -Year denotes dummies for each Cerved Altman Z-score $\times$ year. Standard errors presented in parentheses are clustered at the province level. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Default Rate						
	Firm	Province		Bank-Province			
Overconfidence	0.240*** (0.0510)	0.222*** (0.078)	0.294*** (0.077)	0.020*** (0.005)			
BankColl _{<i>b,t-1</i>}				-0.049*** (0.014)	-0.046*** (0.014)		
Overconfidence $\times$ BankColl _{<i>b,t-1</i>}				0.070*** (0.019)	0.066*** (0.020)	0.033** (0.014)	
Overconfidence $\times$ $\mathbb{1}(\text{BankColl}_{b,t-1} > 0)$							0.008* (0.004)
Firm&Manager Controls	Y	-	-	-	-	-	-
Geographic Controls	-	N	Y	Y	-	-	-
South-Year&North-Year FE	-	Y	Y	Y	-	-	-
Industry-Year FE	Y	-	-	-	-	-	-
$\mathbb{1}(\text{Credit Score})$ -Year FE	Y	-	-	-	-	-	-
Prov-Year FE	Y	N	N	N	Y	Y	Y
Bank-Year FE	-	-	-	N	N	Y	Y
Observations	380065	1414	1414	111628	124191	123882	123882
R ²	0.0583	0.247	0.274	0.014	0.035	0.221	0.221

Online Appendix

Lending to Overconfident Borrowers

FILIPPO DE MARCO, JULIEN SAUVAGNAT, AND ENRICO SETTE

Figure A.1: **Forecast Errors and Default**

This scatter plot reports the relationship between the firm forecast error on future sales and the 1-year probability of default separately for the subsample of observations with negative and positive forecast errors. Each dot represents an equal-sized bin of firm forecast errors (100 bins). The vertical dashed line indicates a forecast error of zero.

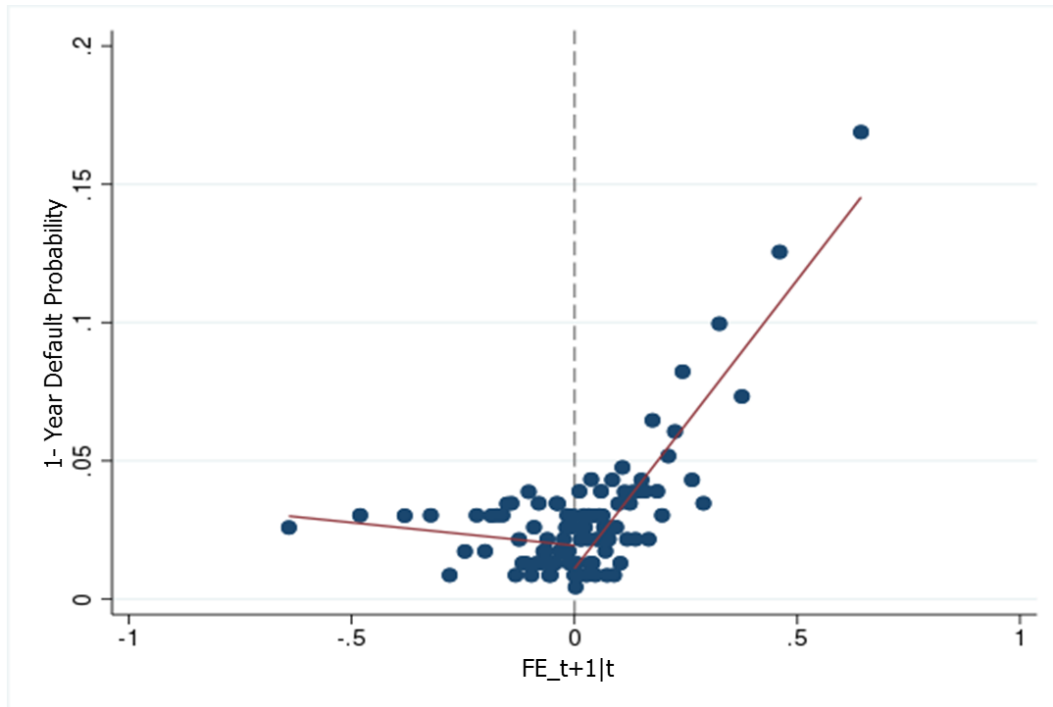


Figure A.2: INVALSI Survey

This is an extract from the Italian Ministry of Education and the National Institute for the Evaluation of the Italian Education System (INVALSI) questionnaire (“Questionario Studente”) in which students are asked “What do you think about mathematics” (“Che cosa pensi della Matematica”), with a simple yes (“sì”) or no (“no”) answer to a set of sub-questions. Specifically, our analysis exploits Question 15.B: *La Matematica è più difficile per me che per molti miei compagni* which reads as *mathematics is harder for me than for many of my classmates*.



Ministero dell'Istruzione
dell'Università e della Ricerca



Istituto nazionale per la valutazione
del sistema educativo di istruzione e di formazione

Rilevazione degli apprendimenti

Anno Scolastico 2008 – 2009

QUESTIONARIO STUDENTE

Scuola Primaria
Classe Quinta

Spazio per l'etichetta autoadesiva

15. Che cosa pensi della matematica?
Metti una crocetta su un solo quadratino per ogni riga.

	<i>Sì</i>	<i>No</i>
A. In matematica sono bravo/a	☐	☐
B. La matematica è più difficile per me che per molti miei compagni	☐	☐
C. Imparo facilmente la matematica	☐	☐
D. Mi diverto a fare matematica	☐	☐
E. Mi piacerebbe fare più matematica a scuola	☐	☐

Table A.1: **Overconfidence of Origin versus Firm Location**

This table presents transition frequencies across overconfidence quartiles of the province of origin of managers and the overconfidence quartiles of the firm they join over the sample period. Pupils' overconfidence in each province is first residualized on local geographic controls: the log of average GDP per capita, the length of bankruptcy proceedings, the region-averages from the preference survey in Falk et al. (2018), and a dummy for the South.

Overconfidence of origin	Overconfidence of firm location			
	Q1	Q2	Q3	Q4
Q1	0.282	0.218	0.261	0.239
Q2	0.274	0.286	0.225	0.215
Q3	0.251	0.265	0.231	0.253
Q4	0.218	0.230	0.281	0.272

Table A.2: **Do Overconfident Managers Match With Riskier Firms?**

The unit of observation is a firm-year. The sample is restricted to firm-year observations before a “mover” manager is hired. Movers are defined as senior managers (CEO, CFO and other top executives) who were born in a different province from the one where the firm’s headquarters is located. The dependent variable is the firm credit score in the regression for the results in columns (1)-(2); sales growth volatility in the past three years in the regression for the results in columns (3)-(4); EBITDA over assets in the regression for the results in columns (5)-(6), all measured in the year before the mover joins the firm. Overconfidence is the province-level share of pupils who say that they find mathematics easier than their classmates in the province where the manager was born. Manager characteristics are the geographic controls calculated for the province or region (Falk et al., 2018) of birth of the manager, a female dummy indicator and the (log of) manager’s age. Fixed effects include: Prov-Year denotes province $\times$ year; Industry-Year denotes 2-digit industry $\times$ year; $\mathbb{1}(\text{Credit Score})$ -Year denotes dummies for each Cerved Altman Z-score $\times$ year. Standard errors presented in parentheses are clustered at the province level. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Firm characteristics in the year before mover joins:					
	Credit Score		Vol(Sales Growth)		EBITDA/Assets	
Overconfidence	0.857 (0.903)	0.649 (0.760)	-0.138 (0.274)	-0.046 (0.047)	-0.009 (0.029)	-0.004 (0.025)
Firm&Manager Controls	N	Y	N	Y	N	Y
Prov-Year FE	Y	Y	Y	Y	Y	Y
Industry-Year FE	Y	Y	Y	Y	Y	Y
$\mathbb{1}(\text{Credit Score})$ -Year FE	N	N	Y	N	N	Y
Observations	196148	196148	196148	196148	196148	196148
R ²	0.087	0.132	0.097	0.723	0.092	0.141

Table A.3: **Boys' Overconfidence and Firm Forecast Errors**

The unit of observation is a firm-year. The dependent variable is $\mathbb{1}(FE_{t+1|t} > 0.1)$ in columns (1)-(3), a dummy equal to one if the firm forecast error on future sales growth exceeds 10 percentage points, 0 otherwise, and the firm forecast error on future sales ($FE_{t+1|t}$) in columns (4)-(6). Overconfidence is the share of male pupils who say that they find mathematics easier than their classmates in the province where the manager is born. Firm controls include current realized and past sales growth, sales growth volatility over the past three years, lagged leverage, lagged EBITDA/assets, the log of firm age and firm-age terciles, the log of total assets and quintiles of total assets, the Cerved Altman Z-score index, ranging from 1 (lowest risk) to 9 (highest risk). Manager controls are the same geographic controls calculated for the province or region (Falk et al., 2018) of birth of the manager, a female dummy indicator and the (log of) manager's age. Geographic controls include: region-averages from the preference risk survey in Falk et al. (2018), i.e. Patience, Risk Taking, Positive Reciprocity, Negative Reciprocity, Altruism, and Trust; the log of province-level GDP per capita in each year; the log of the province-average length of bankruptcy proceedings in days. Fixed effects include: South-Year&North-Year denotes macro-areas for north and south $\times$ year; Prov-Year denotes province $\times$ year; Industry-Year denotes 2-digit industry $\times$ year; $\mathbb{1}(\text{Credit Score})$ -Year denotes dummies for each Cerved Altman Z-score $\times$ year. Standard errors presented in parentheses are clustered at the province level. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	$\mathbb{1}(FE_{t+1 t} > 0.1)$			$FE_{t+1 t}$		
Boys' Overconfidence	0.894*** (0.340)	0.855** (0.371)	0.781** (0.360)	0.347*** (0.119)	0.346** (0.132)	0.368** (0.151)
Firm&Manager Controls	Y	Y	Y	Y	Y	Y
Geographic Controls	Y	-	-	Y	-	-
South&North-Year FE	Y	-	-	Y	-	-
Prov-Year FE	N	Y	Y	N	Y	Y
Industry-Year FE	N	N	Y	N	N	Y
$\mathbb{1}(\text{Credit Score})$ -Year FE	N	N	Y	N	N	Y
Observations	11726	11726	11726	11726	11726	11726
R^2	0.263	0.356	0.426	0.549	0.603	0.646

Table A.4: **Overconfidence and Firm Forecast Intervals**

The unit of observation is a firm-year pair. The dependent variable is the difference between the maximum and minimum forecasts of sales growth next year. Overconfidence is the share of pupils who say that they find mathematics easier than their classmates in the province where the manager is born. Firm controls include current realized and past sales growth, sales growth volatility over the past three years, lagged leverage, lagged EBITDA/assets, the log of firm age and firm-age terciles, the log of total assets and quintiles of total assets, the Cerved Altman Z-score index, ranging from 1 (lowest risk) to 9 (highest risk). Manager controls are the same geographic controls calculated for the province or region (Falk et al., 2018) of birth of the manager, a female dummy indicator and the (log of) manager's age. Geographic controls include: region-averages from the preference risk survey in Falk et al. (2018), i.e. Patience, Risk Taking, Positive Reciprocity, Negative Reciprocity, Altruism, and Trust; the log of province-level GDP per capita in each year; the log of the province-average length of bankruptcy proceedings in days. Fixed effects include: South-Year&North-Year denotes macro-areas for north and south $\times$ year; Prov-Year denotes province $\times$ year; Industry-Year denotes 2-digit industry $\times$ year; $\mathbb{1}(\text{Credit Score})$ -Year denotes dummies for each Cerved Altman Z-score $\times$ year. Standard errors presented in parentheses are clustered at the province level. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)
	Upper-Lower Bound		
Overconfidence	0.109 (0.106)	0.017 (0.111)	-0.069 (0.102)
Firm&Manager Controls	Y	Y	Y
Geographic Controls	Y	-	-
South&North-Year FE	Y	-	-
Prov-Year FE	N	Y	Y
Industry-Year FE	N	N	Y
$\mathbb{1}(\text{Credit Score})$ -Year FE	N	N	Y
Observations	3849	3849	3849
R^2	0.092	0.308	0.443

Table A.5: **Forecast Errors and Credit Outcomes**

The unit of observation is a firm-bank-year. The dependent variable is the log of total credit in Panel A; the average interest rate across loan types in Panel B; the share of collateralized credit in Panel C. $\mathbb{1}(FE_{t+1|t} > 0.1)$ is a dummy equal to one if the firm forecast error on future sales growth exceeds 10 percentage points, 0 otherwise. Fixed effects include: Prov-Year denotes province $\times$ year; Industry-Year denotes 2-digit industry $\times$ year; $\mathbb{1}(\text{Credit Score})$ -Year denotes dummies for each Cerved Altman Z-score $\times$ year. Standard errors presented in parentheses are clustered at the firm level. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)
Panel A. Log(Credit)			
$\mathbb{1}(FE_{t+1 t} > 0.1)$	-0.101*** (0.032)	-0.092*** (0.032)	-0.127*** (0.030)
Observations	23134	23112	23000
R^2	0.068	0.139	0.271
Panel B. Average Loan Rate (%)			
$\mathbb{1}(FE_{t+1 t} > 0.1)$	0.341*** (0.039)	0.315*** (0.041)	0.158*** (0.039)
Observations	15679	15656	15593
R^2	0.237	0.310	0.390
Panel C. Share Collateralized Credit			
$\mathbb{1}(FE_{t+1 t} > 0.1)$	1.678*** (0.318)	1.731*** (0.323)	1.163*** (0.309)
Year FE	Y	-	-
Prov-Year FE	N	Y	Y
Industry-Year FE	N	N	Y
$\mathbb{1}(\text{Credit Score})$ -Year FE	N	N	Y
Observations	23134	23112	23000
R^2	0.021	0.083	0.200

Table A.6: **Overconfidence and Loan Rates: Robustness**

The dependent variable is the average interest rate at the firm-year level on overdrafts in Panel A, on credit lines backed by receivables in Panel B and term loans in Panel C. Overconfidence is the share of pupils who say that they find mathematics easier than their classmates in the province where the manager is born. Firm controls include current realized and past sales growth, sales growth volatility over the past three years, lagged leverage, lagged EBITDA/assets, the log of firm age and firm-age terciles, the log of total assets and quintiles of total assets, the Cerved Altman Z-score index, ranging from 1 (lowest risk) to 9 (highest risk). Manager controls are the same geographic controls calculated for the province or region (Falk et al., 2018) of birth of the manager, a female dummy indicator and the (log of) manager's age. Geographic controls include: region-averages from the preference risk survey in Falk et al. (2018), i.e. Patience, Risk Taking, Positive Reciprocity, Negative Reciprocity, Altruism, and Trust; the log of province-level GDP per capita in each year; the log of the province-average length of bankruptcy proceedings in days. Fixed effects include: South-Year&North-Year denotes macro-areas for north and south $\times$ year; Prov-Year denotes province $\times$ year; Industry-Year denotes 2-digit industry $\times$ year; 1(Credit Score)-Year denotes dummies for each Cerved Altman Z-score $\times$ year; Standard errors presented in parentheses are clustered at the province level. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)
	Panel A. Overdrafts		
Overconfidence	7.996*** (0.939)	5.558*** (0.713)	4.984*** (0.723)
Observations	457862	457862	457649
R^2	0.127	0.139	0.184
	Panel B. Account Receivables Credit		
Overconfidence	2.645*** (0.726)	0.633 (0.510)	1.491*** (0.463)
Observations	457862	457862	457649
R^2	0.098	0.113	0.262
	Panel C. Term Credit		
Overconfidence	0.871* (0.451)	1.257*** (0.333)	1.209*** (0.341)
Firm&Manager Controls	Y	Y	Y
Geographic Controls	Y	-	-
South-Year&North-Year FE	Y	-	-
Prov-Year FE	N	Y	Y
Industry-Year FE	N	N	Y
1(Credit Score)-Year FE	N	N	Y
Observations	457862	457862	457649
R^2	0.105	0.117	0.138

Table A.7: **Bank Reliance on Collateral: Persistence and Bank Characteristics**

The dependent variable is the estimated bank-year fixed effects from Eq. (3). HQ South refers to a dummy equal to one for banks headquartered in the South. Regressions are weighted using bank total assets. Standard errors presented in parentheses are clustered at the bank level. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)
	BankColl _{<i>b,t</i>}		
BankColl _{<i>b,t-1</i>}	0.799*** (0.027)		0.787*** (0.032)
CapRatio _{<i>b,t-1</i>}		0.0015 (0.0069)	-0.0005 (0.0013)
NPL/Assets _{<i>b,t-1</i>}		-0.0007 (0.0007)	-0.0003 (0.0002)
log(Assets) _{<i>b,t-1</i>}		-0.0040 (0.0056)	-0.0015 (0.0009)
Cooperative Bank		0.0119 (0.0196)	-0.0003 (0.0027)
HQ South		0.0161 (0.0122)	0.0026 (0.0026)
Year FE	Y	Y	Y
Observations	3521	3521	3521
R ²	0.821	0.827	0.952

Table A.8: **Overconfidence and Collateral: Crisis and Post-crisis robustness**

The unit of observation is a firm-year. The dependent variable is the logarithm of total credit. Overconfidence is the share of pupils who say that they find mathematics easier than their classmates in the province where manager is born. $\text{ShareColl}_{f,t-1}$ is the lagged firm's share of collateralized term credit, scaled by its standard deviation. Firm controls include current realized and past sales growth, sales growth volatility over the past three years, lagged leverage, lagged EBITDA/assets, the log of firm age and firm-age terciles, the log of total assets and quintiles of total assets, the Cerved Altman Z-score index, ranging from 1 (lowest risk) to 9 (highest risk), and the non-interacted term $\text{ShareColl}_{f,t-1}$. Manager controls are the same geographic controls calculated for the province or region (Falk et al., 2018) of birth of the manager, a female dummy indicator and the (log of) manager's age. Geographic controls include: region-averages from the preference risk survey in Falk et al. (2018), i.e. Patience, Risk Taking, Positive Reciprocity, Negative Reciprocity, Altruism, and Trust; the log of province-level GDP per capita in each year; the log of the province-average length of bankruptcy proceedings in days. Fixed effects include: Prov-Year denotes province $\times$ year; South-Year&North-Year denotes macro-areas for north and south $\times$ year; Industry-Year denotes 2-digit industry $\times$ year; $\mathbb{1}(\text{Credit Score})$ -Year denotes dummies for each Cerved Altman Z-score $\times$ year. Standard errors presented in parentheses are clustered at the province level. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

	(1) 2005–2007	(2) 2008–2012	(3) 2013–2017
Overconfidence	-0.550** (0.222)	-0.912*** (0.185)	-0.621*** (0.217)
Overconfidence $\times$ ShareColl $_{f,t-1}$	0.178 (0.128)	0.377*** (0.121)	0.369** (0.182)
Firm&Manager Controls	Y	Y	Y
Prov-Year FE	Y	Y	Y
Industry-Year FE	Y	Y	Y
$\mathbb{1}(\text{Credit Score})$ -Year FE	Y	Y	Y
Observations	77,958	164,148	149,282
R^2	0.801	0.790	0.770