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Abstract

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JEL Classification: G41, G21

Keywords: Optimism, Business expectations, Loan applications, Borrower default, Collateral requirements

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December 28, 2022

Abstract

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1 Introduction

There is ample evidence that business owners and top executives are prone to excessive confidence in their own abilities.[1] Several studies have explored the implications of managerial overconfidence on a number of corporate outcomes, such as over-investment, risky acquisitions and debt maturity (Malmendier and Tate, 2005, 2008; Landier and Thesmar, 2008; Ben-David et al., 2013). There is however limited evidence on whether banks incorporate borrowers' overconfidence in their lending decisions.[2] Understanding how banks lend to overconfident borrowers is crucial to estimate the economic impact of overconfidence, as bank lending may amplify or reduce the potential distortions associated with overconfidence.

Investigating the effects of borrowers' overconfidence on credit outcomes poses two main empirical challenges. First of all, overconfidence – when measured, for instance, through managers' tendency to make positive forecast errors on future performance – is likely to be endogenous to other unobserved factors.[3] In fact, positive forecast errors might reflect not only overconfidence, but also the occurrence of unexpected negative shocks that can induce rational errors ("bad luck"). Second, if overconfident borrowers invest in value-destroying projects (Malmendier and Tate, 2008), it may be difficult to distinguish their credit outcomes from those of borrowers with high credit risk. In this paper, we address both empirical challenges and provide novel evidence on the impact of borrowers' overconfidence on banks' credit supply decisions and ultimately on corporate investment and default.

We measure credit supply decisions using granular data on acceptance rates for corporate loan applications, together with bank-firm credit volumes and interest rates from the Italian

[1] Overconfidence may refer to two different concepts: miscalibration or overplacement. Miscalibration is the excessive confidence in having accurate information, whereas overplacement is the belief of being better than others ("better-than-average" effect). We refer to overconfidence using the latter definition (as in Malmendier and Tate, 2005).

[2] Previous work on financial contracting with overconfident or optimistic managers is mostly theoretical (see 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.

[3] There are two common ways to measure managerial overconfidence: 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.

Credit Register. To identify the effect of overconfidence on loan outcomes, we exploit variation across areas in Italy in the share of local pupils who claim that they find Mathematics easier than their classmates.[4] In line with prior work showing that historical or cultural factors, such as ethnicity, customs and local traditions, affect current beliefs and attitudes (Guiso et al., 2016; D'Acunto et al., 2019; Michalopoulos and Xue, 2021), we consider overconfidence to be a local cultural trait, so that pupils' overconfidence will also reflect the intrinsic overconfidence of borrowers born in the same area. Using pupils' overconfidence as opposed to managers' forecast errors allows us to achieve identification because students' self-reported ability is plausibly unrelated to contemporaneous economic shocks.

To guide our empirical investigation, we formulate a simple model of bank lending to overconfident borrowers. We follow prior work (e.g Landier and Thesmar, 2008), and assume that overconfident entrepreneurs (wrongly) interpret bad news on their projects as being good. We derive credit outcomes depending on bank collateral requirements in a setting where competitive banks are able to observe whether borrowers are overconfident or not.[5] In fact, while collateral requirements typically mitigate asymmetric information problems in credit markets (e.g. Bester, 1985; Besanko and Thakor, 1987), the same is not true when borrowers are overconfident, i.e. they are unaware of the risk they take, resulting in over-borrowing and higher ex-post default (Manove and Padilla, 1999). The model delivers three key empirical predictions: overconfident borrowers on average (i) make positive forecast errors on future revenues; (ii) are less likely to be denied credit by banks when they have to pledge collateral, in which case (iii) they are more likely to invest and default.

We first show that pupils' overconfidence is not correlated with other risk and social preferences (Falk et al., 2018), economic development, law inefficiency or social capital

[4] We obtain pupils' self-reported overconfidence from a questionnaire in the national education attainment test (INVALSI). This measure is motivated by a large literature in psychology showing that students systematically over-estimate their performance in exams (e.g. Hacker et al., 2000). Consistent with the presence of a "better-than-average" effect, 72% of Italian students are overconfident in their ability in Mathematics, but with significant variation across provinces. Provinces are geographical areas similar in size to US counties.

[5] Banks can have better private information on the borrowers' type than the borrowers themselves, because of their lending experience and the benefit of detachment (Inderst and Mueller, 2006).

(Guiso et al., 2004) once macro-area indicators are included.[6] Thus, the residual variation in overconfidence after controlling for these characteristics, is plausibly exogenous with respect to other contemporaneous economics shocks that affect local firms. We then document a robust relationship between pupils' overconfidence and the likelihood of local borrowers to issue overly-optimistic forecasts on their future sales growth. A borrower located in an area with the highest level of overconfidence has a 27% higher probability of making a large positive forecast error compared to a borrower from the least overconfident area. We saturate the regression with an extensive set of industry-year, credit rating-year and macro area-year fixed-effects to absorb time-varying unobserved shocks that may also cause forecast errors to be higher. Moreover, we show that pupils' overconfidence affects managers' rosy views about their own firm's future performance, but not those about the overall Italian economy, or with the forecast min-max range. Our approach therefore isolates overconfidence about the firm's prospects from other determinants of beliefs, such as optimism (Puri and Robinson, 2007) or miscalibration (Ben-David et al., 2013).

A potential concern is that some other local factor, beyond the economic and social ones already included in our specifications, could be driving 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 (as for example in Guiso et al., 2021), and test whether the overconfidence of the place of birth of the managers still matters for corporate outcomes. This can happen if current expectations are affected by past experiences, which in turn depends on location (Malmendier and Nagel, 2011). Since the majority of managers and entrepreneurs in Italy work in the same province where they were born (Baltruinate et al., 2019), focusing on movers reduces our sample by more than two thirds. In this restricted sample, however, we can control for time-varying unobserved heterogeneity of the area where the firm is located using province-year fixed-effects. Reassuringly, we find similar results. Importantly, we check and

[6] Macro-area indicators are dummies for the North and South of the country. The South of Italy is characterized by low levels of social capital and trust (Guiso et al., 2004), low income levels and poor legal enforcement.

find that movers born in highly overconfident areas end up in firms with ex-ante similar characteristics to those born in low overconfidence areas. This mitigates the concern that the matching of overconfident managers with firms of certain characteristics could have confounded the interpretation of our results in the movers sample.

We then investigate the effects of borrowers' overconfidence on credit outcomes and find that banks restrict credit to overconfident borrowers. We document that borrowers from the most overconfident areas pay 20% higher interest rates on their loans, have a 29% higher share of credit backed by collateral and their loan applications are 11% less likely to be accepted compared to borrowers from the least overconfident areas. This result is consistent with the notion that lenders, having statistically accurate information or specialized lending portfolios, are in a better position than the borrower itself to evaluate the riskiness of the project (Manove et al., 2001; Inderst and Mueller, 2006).[7]

Next, we ask whether collateral requirements reinforce or mitigate credit rationing for overconfident borrowers. Empirically, we capture bank-specific ability to recover collateral using a unique Bank of Italy survey on bank lending practices towards first-time borrowers. We find that banks that value collateral as the most important factor in their lending decisions – and hence specialize in collateral-based lending – are 16% more likely to accept loan applications from overconfident borrowers compared to banks that value collateral as the least important factor. The results are not confounded by differences in other bank characteristics or borrowers' credit risk: we do not find that collateral-based banks lend more to firms with high credit risk, but only to overconfident borrowers, as predicted by our model.

We also explore the real implications of our findings for corporate investment and default. Previous work has shown that overconfident managers invest more than rational managers.[8]

[7] We also address the concern that our results are driven by local bank overconfidence. First of all, we note the direction of bias, if any, is not clear a priori: loan officers who overestimate their ability to screen may have either higher or lower acceptance rates. Second we include bank-year fixed-effects, absorbing all unobserved heterogeneity at bank-time level. Finally, we repeat the analysis and find similar results within the sub-sample of large banks, whose lending decisions tend to follow uniform rules taken at the headquarter level (Liberti et al., 2016).

[8] See Goel and Thakor (2008) for a theoretical treatment, and Malmendier and Tate (2005) or Ben-David et al. (2013) for empirical evidence.

Our novel contribution is to show that the sensitivity of investment to overconfidence is amplified by the collateral lending channel: the investment rate of overconfident borrowers is higher only when they borrow from collateral-based banks. Crucially, this does not hold for borrowers with high credit risk, who invest and default less when they borrow from collateral-based banks. This is consistent with the theoretical prediction that collateral requirements mitigate moral hazard when borrowers are rational and aware of their types, but not when they have biased beliefs (Manove and Padilla, 1999). We thus shed light on the instrumental role of banks in shaping how managers' overconfidence affect economic outcomes.

Finally, we estimate the amount of loan losses due to overconfidence that would have been avoided if banks did not rely as much on collateral in lending to first-time borrowers. We find that bad loans (i.e. non-performing loans to insolvent borrowers) could have been €10 billion lower in 2017 if banks relied less on collateral when lending to overconfident borrowers. This represents 8% of total bad loans to non-financial firms in Italy in 2017 and it is a conservative estimate since even banks with the lowest reliance on collateral could still use collateral requirements in lending decisions. Moreover, recovery rates on bad loans to non-financial firms are 37% even when loans are secured collateral. That is, requiring collateral does not allow to fully recover the value of the loan when the borrower is in distress. These results suggest that the collateral lending channel matters quantitatively to 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 studying 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, 2022), risk-taking and innovation (Galasso and Simcoe, 2011; Hirshleifer et al., 2012), and firm value (Malmendier and Tate, 2008; Barrero, 2022).[9] There is also a fast-growing literature studying the implications of lenders' biased beliefs for the economy, especially in the context of boom and bust episodes (see e.g. Greenwood and Hanson, 2013; Bordalo et al.,

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

2018; Ma et al., 2020; Carvalho et al., 2021). Compared to these papers, we provide the first empirical evidence that banks' credit supply decisions are key to understand the real effects of overconfidence on corporate outcomes.

We also add to a stream of mostly theoretical work on financial contracting with managers holding biased beliefs (see e.g. de Meza and Southey, 1996; de Meza, 2002; Heaton, 2002; Coval and Thakor, 2005; Sandroni and Squintani, 2007; Hackbarth, 2008). Empirically, Landier and Thesmar (2008) show that optimistic managers may naturally self-select into short-term debt, a prediction which they confirm with French survey data. Using data from U.S. publicly listed firms, Otto (2014) finds evidence 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) that they pay lower loan spreads. Fecht and Opaleva (2019) 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 exploit credit-registry data, and provide evidence on how borrowers' overconfidence, measured through pupils' overconfidence, affects banks' credit supply.

Finally, our results provide novel insights for the literature studying 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 (Boot and Thakor, 1994; Thakor and Udell, 1991). Consistent with the predictions of ex-post theories, empirical studies document 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). While we confirm in our data that observably high credit risk borrowers indeed invest less when required to pledge collateral, our contribution is to provide the first empirical evidence on the distortionary effects of collateral through borrowers' overconfidence.

2 Theoretical Framework

Defining overconfidence. 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 (see e.g. Ben-David et al., 2013). The illusion of control refers to the tendency of individuals to overestimate their ability to control events over which they have limited influence (see e.g. Langer, 1975). Overplacement is instead the tendency of people to believe themselves to be better than their true quality and overplace their performance relative to 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 e.g. in Malmendier and Tate (2005, 2008).

Overconfidence, collateral requirements, and credit markets. Theory highlights that credit markets may be characterised by excessive lending when managers have overconfident beliefs about the future prospects of their firms (de Meza and Southey, 1996; de Meza, 2002; Manove and Padilla, 1999). This is because overconfidence leads managers to (wrongly) perceive negative net-present-value (NPV hereafter) projects as being profitable (Heaton, 2002). Importantly, as shown in Manove and Padilla (1999), when borrowers have biased beliefs about their projects, collateral requirements can reduce credit market efficiency by inducing banks to lend to overconfident borrowers who then invest in value-destroying projects. This is in sharp contrast with the theoretical findings that collateral requirements typically mitigate lending frictions, such as adverse selection ex-ante (Bester, 1985; Besanko and Thakor, 1987),[10] and moral hazard ex-post (Boot and Thakor, 1994; Thakor and Udell, 1991). In particular, when self-conscious risky borrowers are required to pledge collateral, this encourages them to shift into safer investment projects, and to default less (Ioannidou

[10] When credit risk is firms' private information, collateral allows banks to screen borrowers, that is those with higher-quality projects choose debt contracts with collateral and low interest rates, and those with lower-quality projects self-select into unsecured debt and high interest rates.

et al., 2022). Instead, asking for collateral is not a good screening device for overconfident borrowers, who by definition they are not conscious of their own biases, and end up investing and defaulting more when they receive credit.

We provide below a simple theoretical framework to formalize these intuitions. For this, we build a stripped down version of a model of bank lending to overconfident borrowers. This model generates predictions that will guide our empirical analysis in the rest of the paper. In particular, we show that overconfident borrowers on average: (i) make positive forecast errors on their future revenues; (ii) are more likely to be receive credit by banks when they have to pledge collateral, in which case (iii) they are more likely to invest, and to default ex-post.

Model of bank lending to overconfident borrowers. The model has three periods. At time $t = 0$ the entrepreneur, with asset in place A, has a project that costs I and it looks for external financing from a set of competitive banks. The return for the entrepreneur depends on two factors: i) the project type, which can be "Good" ("Bad") with probability α $(1 - \alpha)$; ii) the strategy chosen at time $t = 1$, which is either "Growth" or "Safe". The Growth strategy gives R_{Gr} if the project is Good, 0 otherwise. The Safe strategy instead gives R_S in both cases. We assume that $R_{Gr} > R_S > I$, but $(1 - \alpha)R_{Gr} < I$, i.e. adopting the Growth strategy for both good and bad projects results in a negative NPV project. The project type is unobserved by banks while we assume for simplicity that the entrepreneur receives at time $t = 0$ a perfectly informative private signal on the project's type.

Following prior work in the literature (e.g Manove and Padilla, 1999; Landier and Thesmar, 2008), we assume that entrepreneurs have two types of beliefs: "realistic" entrepreneurs have correct priors about the project's quality and update it using Bayes' rule; "overconfident" entrepreneurs instead always believe their project is good, regardless of the signal they receive. Thus, a realistic entrepreneur will choose the Growth strategy if the project is Good and the Safe strategy if the project is Bad. Overconfident entrepreneurs instead always want to implement the Growth strategy. At time $t = 2$ payoffs are realized.

We assume that banks are competitive and derive credit outcomes in the case where banks are "sophisticated", i.e., they observe whether borrowers are overconfident or not, borrowing the notion of informed lending from Inderst and Mueller (2006).[11] Moreover, we assume that banks do not observe the signal about the quality of the project and the strategy is not contractible. The debt contract specifies a promised repayment at $t = 2$, denoted by R^{Bank}, and collateral requirements ($\chi < 1$) on the firm's asset in place $A < I$, which are seized in case of default (i.e. $\chi A < A$). The fraction χ can be interpreted as an intrinsic characteristic of the asset (say tangibility) or the recovery value, which depends on bank-specific ability to recover collateral.

Credit outcomes with and without collateral. Because banks are sophisticated, they anticipate that overconfident borrowers will always find optimal to implement the Growth strategy. It follows that banks' zero-profit condition is:

$$(1-\alpha)R^{Bank} + \alpha\chi A = I \rightarrow R^{Bank} = \frac{I - \alpha\chi A}{1-\alpha} > I$$

When the project is good, banks will receive the promised repayment R_{Bank} while they will seize firms' assets when the project is bad (and the overconfident borrower implements the growth strategy).[12] Overconfident borrowers' (perceived) ex-ante profits are given by $\Pi^{overconfident} = R_{Gr} - R^{Bank}$. Plugging the value of R^{Bank} from above, we get:

$$\Pi^{Overconfident} = \underbrace{(R_{Gr} - I)}_{\text{NPV from overconfident borrower's perspective}} - \underbrace{\alpha\left(\frac{I-\alpha\chi A}{1-\alpha}\right)}_{\text{cost of external finance}}$$

Because an overconfident borrower always perceives signals as being good, (s)he believes

[11] Banks might have better private information on the borrowers' type than the borrowers themselves, because of their lending experience and the benefit of detachment. Alternatively, one could assume that banks are "naive" - they think that all borrowers are realistic. In that case, they anticipate that borrowers will implement the Safe strategy when the signal is bad. Banks' (perceived) zero-profit condition is $\tilde{R}_{Bank} = I$, and overconfident borrowers' perceived ex-ante profits are equal to: $\Pi^{Overconfident} = R_{Gr} - I$. It follows that overconfident borrowers' projects are financed, and naive banks bear the losses associated to their bad investment decisions. Bank losses ex-post are equal to $\alpha\,(I - \chi A) > 0$.

[12] It follows from the expression of R_{Bank} that the interest rate charged by sophisticated banks to overconfident borrowers is $r = \frac{\alpha}{1-\alpha}\left(1 - \chi\frac{A}{I}\right) > 0$, which is increasing in α, the ex-ante probability that the project is bad, and decreasing in χ, the value of firms' collateral from banks' perspective.

that the realized return at $t = 2$ will be R_{Gr}, regardless of the quality of the project. Note that the cost of external finance is decreasing in χ. When collateral requirements are not present ($\chi = 0$), $\Pi^{Overconfident}$ is negative and overconfident borrowers are credit-constrained (for their own good). Instead, when χ is large enough, overconfident borrowers might obtain bank financing and invest in negative NPV projects. It follows that collateral requirements reduce lending efficiency when borrowers are overconfident about the quality of their projects.

3 Data and Stylized Facts on Overconfidence

We use different sources of information, and report summary statistics in Table 1. We describe each of these in more details below, and discuss the summary statistics of each dataset in the relevant section of the empirical analysis. The sample period is 2001-2017.

[INSERT TABLE 1 HERE]

3.1 Data from the Italian ministry of education

To isolate the effect of corporate overconfidence on credit outcomes we exploit differences in overconfidence across areas in Italy using INVALSI, the national standardized test in Italian and Mathematics, introduced in 2009 to evaluate school productivity and compulsory for all primary school students in Italy (age 9-11).[13] We obtain the individual students' answers for three waves (2009-2010, 2011-2012, 2012-2013).

In a related questionnaire students are asked to report their beliefs about their own ability in Mathematics relative to their classmates , with a simple yes or no answer to question 15.B: *"Mathematics is harder for me than for many of my classmates"* (see Figure A.1 in the Online Appendix). We define pupils' overconfidence as the fraction of pupils who answer "no" to the above question, and therefore by construction those who believe that "Mathematics is

[13] Italy is divided in 20 regions and each region is further subdivided into provinces, each surrounding a city. The number of provinces is between 101 and 110 in the period 2001-2017.

easier (or equally easy) for me than for many of my classmates". Admittedly, the presence of students who find Mathematics equally easy and answer "no" to the above question will lead us to overestimate the *level* of pupils' overconfidence in a given province.[14] Still, as long as there are no differences *across* provinces in the share of students who find Mathematics equally easy, this is not a threat to our empirical strategy, as we exploit cross-sectional variation in overconfidence across provinces in Italy. Similarly, while it is well known that girls exhibit lower self-confidence in Mathematics (Carlana, 2019), differences in overconfidence between girls and boys are not a concern for our results because the sex ratio is balanced across provinces.

Crucially for the interpretation of our empirical findings, this question allows us to isolate overconfidence – the tendency of pupils to overestimate their own ability *relative* to their peers – from other confounding factors, such as local differences in what is perceived to be a good grade in Mathematics, a phenomenon, especially present in the South of Italy, which is known as "grade inflation".[15]

3.2 Credit register (loan applications, interest rate, default)

Detailed data on credit are obtained from the Italian Credit Register (CR), which is maintained by Bank of Italy. The CR tracks the amount of credit between each bank and firm for credit exposures over €75,000 for three types of credit: overdraft (i.e. unsecured, uncommitted,

[14]Generally speaking though, other answers to the questions on the INVALSI questionnaire point in the direction of students' overconfidence. For example, 72% of Italian students answer "no" to question 15.B (*"Mathematics/Italian is harder for me than for many of my classmates"*), 78% answer "yes" to 15.A ("*I am good in Mathematics*") and 67% answer "yes" to 15.C ("*I learn Mathematics easily*"). In untabulated tests, we confirm that all our key results on credit and collateral requirements hold if we use the answers to these questions as alternative measure of pupils' overconfidence.

[15]Take for instance the yes or no answer to question 15.A *"I am good in Mathematics"*. This measure could be confounded by differences in grade inflation across Italian areas. To see this, consider Sara and Giulia, who live in different part of the country but have the same exact math abilities. Sara (North) typically gets 5/10 in math while Giulia (South) typically gets 7/10, because her math teacher is a more generous grader. These differences in average grades could lead Sara to answer "no" to the question "I am good in Mathematics" while Giulia would answer "yes". In this case, however, Giulia has unbiased beliefs about her perception of Mathematics, based on the results that she normally obtains in class. Instead, when asked about whether "Mathematics is harder for me than for many of my classmates", the answer depends on relative ranking within class, and irrespective of the level grade, Sara and Giulia will have a similar distribution of classmates above and below them. We thank Francesco D'Acunto for providing us with this example.

revolving lines of credit), credit lines backed by trade receivables and term loans.[16] We also have information on loan applications: these are requests about individual borrowers' credit history (*richiesta di prima informazione*) that banks file with the CR when first-time borrowers apply for a loan. We then observe whether new bank-firm relationships (i.e. positive amount of credit) are created in the quarter after the bank requests to determine whether the application was accepted.

Moreover, banks must report to the CR when they classify a loan as "bad debt", meaning that the borrower is insolvent or in substantially similar circumstances.[17] We measure default as a dummy equal to one if in year $t+1$ the firm existing credit exposure is classified as bad debt by the bank. Finally, the CR includes information on the amount of credit backed by real guarantees at the bank-firm level.

Data on interest rates are collected 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 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 (overdrafts, credit lines backed by receivables and term loans).

3.3 Survey on banks' lending practices

To measure bank collateral requirements, we exploit a confidential survey on bank organizational structures and lending practices which was administered by Bank of Italy in 2006. More than 300 banks participated in the survey, accounting for around 85% per cent of the overall Italian banking system's lending to firms.[18] Banks were asked to report a number of information about their internal organizations, including their lending practices for first-time

[16] The threshold was lowered to €30,000 in December 2008. For consistency, we apply the €75,000 threshold throughout our sample period (2001-2017).

[17] Bad debt ($sofferenza$) 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).

[18] Even though these bank-survey measures are only available for 2006, bank culture and business models are considered to be time-invariant (Fahlenbrach et al., 2012). Moreover, we verify that banks' answers to the survey in 2006 affect loan portfolio throughout our sample period (see Table A.1 in the Online Appendix).

borrowers (question B3 in the survey, reproduced in the Online Appendix Figure A.2). Specifically, banks were asked to rank the relative importance of six factors when they grant credit to a first-time borrower. These factors are related to quantitative or qualitative information or collateral requirements (i.e. personal or real guarantees). We exploit the heterogeneity across banks in the relative importance of collateral requirements in their lending decisions: Figure 1 shows the distribution across all banks participating in the survey in 2006.

3.4 Survey evidence on borrower overconfidence

INVIND. The Survey on industrial and service firms (INVIND), administered by Bank of Italy local branches over the phone or on-site between February and April of each year, asks firm managers to report their forecast of next year (i.e. end of current fiscal year in December) sales, investment, and employment. INVIND is available from 1972, but we use data from 2001 to 2017, when around 4,000 firms in both manufacturing and service sectors are included in each year. We restrict the sample to firms present in the survey for at least three consecutive years. Survey respondents are typically the Chief Financial Officer (CFO) or other senior financial officers for large firms and the Chief Executive Officer (CEO) for small firms (firms in INVIND have a minimum of 20 and a maximum of 153,000 employees). The individual answers to the survey are confidential and are released to the public for statistical purposes in aggregate form only.[19] Having access to confidential answers attenuates the concern that managers have strategic reasons for over-reporting future sales, as it is typically the case for earnings guidance data (Cain et al., 2007). The firm-level information contained in the survey is not available to banks, but only to Bank of Italy.

We also 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 (*codice fiscale*) of managers. We restrict our attention to senior level managers of the firm, such as the CEO, CFO, or Director of sales,

[19]As econometricians, we do not observe the exact identity of the respondent. See Guiso and Parigi (1999) and Ma et al. (2019) for previous work using the same survey and more information on the data.

which are the survey respondents in INVIND. From the tax identifier we are then able to identify the place of birth of the manager, as well as age and gender.

Measuring overconfidence using expectation data. 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 corporate overconfidence. In particular, we compute the sales growth forecast error as the difference between the firm's subjective forecast $F_t(\cdot)$ and future actual sales over current sales: $FE_{t+1|t} = F_t(SalesGr_{t+1}) - SalesGr_{t+1}$, where $SalesGr_{t+1} = Sales_{t+1}/Sales_t$. To measure future and current actual sales we use the figures reported in the official company accounts (Cerved), which include balance sheet data for all Italian limited liability companies.

In Panel A of Table 1, we show that on average managers are quite precise, predicting sales growth to be 1.7 percentage points higher than they actually are. However a significant fraction (24%) 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 Figure A.3 in the Online Appendix, firms with managers that make positive forecast errors in INVIND are also unconditionally more likely to default than other firms.[20] We confirm that this relationship holds in a multivariate regression of default on $\mathbb{1}(FE_{i,t+1|t} > 0.1)$, a dummy equal to one for firms with forecast errors in excess of +10 percentage points, controlling for firm characteristics and time-varying fixed-effects for the industry and credit-score (see Table A.2 in the Online Appendix).

In conclusion, the following stylized facts emerge from survey evidence: i) a significant fraction of firms makes large positive forecast errors and ii) firms with large forecast errors are more likely to default on their loans. These two stylized facts could be explained by negative shocks that cause both higher default and higher forecast errors at some firms and not others. In what follows, we propose an identification strategy to address this concern.

[20]Strikingly, the figure also shows a strong asymmetric effect: the correlation with default is positive only for those with $FE_{t+1|t} > 0$, while it is zero for those for which $FE_{t+1|t} < 0$.

SIGE. The Survey on Inflation and Growth Expectations (SIGE) is a quarterly survey on a representative sample of firms employing 50 or more workers in Italy. In recent years, each wave has about 1,000 firms (Coibion et al., 2019). We exploit two questions. The first is about the own company's prospects: *"The business conditions for your company, in the next 3 months will be?"* The respondent can give three possible answers, taking values from 1 to 3: worse, stable, better. Second, firms in the SIGE are asked about other aggregate economic outcomes, specifically: *"The probability of future improvement in Italy's general economic situation in the next 3 months is".* This question has six possible answers, coded as values from one to six: 0, 1-25 percent, 26-50 percent, 51-75 percent, 76-99 percent and 100 percent.

4 Identification strategy

In order to isolate the impact of borrowers' overconfidence on credit outcomes, we construct a plausibly exogenous measure of overconfidence using differences across areas in Italy in pupils' self-declared ability in Mathematics relative to their classmates.[21] We hypothesize that pupils' overconfidence about their own ability in Math will also reflect the intrinsic overconfidence of local borrowers. This 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 Italian cities that achieved self-government in the Middle Ages have a higher levels of self-efficacy today (i.e. the beliefs in one's own ability to complete tasks) as measured by pupils' answers to the INVALSI survey. D'Acunto et al. (2019) show that households in counties where historical antisemitism was higher express lower trust in finance even today. Consistent with the idea that overconfidence is a persistent local cultural trait, we show in the Online Appendix Table A.3 that the share of overconfident students in Mathematics is strongly correlated across

[21]A similar strategy, using health rather than education outcomes, has been proposed by Puri and Robinson (2007). 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.

different waves of the INVALSI survey.[22]

Formally, we estimate the following equation at the firm-bank-year level:

$$Y_{i,b,t} = \beta \text{Overconfidence}_{\text{Math},p} + \gamma' X_{i,t-1} + \mu' X_p + \lambda_{j,t} + \lambda_{k,t} + \lambda_{b,t} + \epsilon_{i,b,t} \tag{1}$$

where $Y_{i,b,t}$ is a credit outcome between firm i and bank b (e.g. interest rate, share of credit backed by collateral or acceptance rate on loan application), and $\text{Overconfidence}_{\text{Math},p}$ is the share of pupils who say they are better than their classmates in Mathematics in province p where the firm operates. $\lambda_{j,t}$ is a 2-digit industry×year fixed-effect, $\lambda_{k,t}$ is a macro-area year fixed-effect to allow for time-varying shocks i different areas and sectors. $\lambda_{b,t}$ is a bank×year fixed-effect that absorbs all time-varying shocks at bank level. In all regressions, standard errors are clustered at the province level to account for serial correlation of the error term within provinces. $X_{i,t-1}$ is a vector of firm characteristics (current realized and past growth rate of sales, sales growth volatility in the past three years, EBITDA/assets, the log of firm age and total assets; the Cerved Altman credit score).

[INSERT TABLE 2 HERE]

Formally, identification rests on the assumption that, conditional on controls, pupils' overconfidence in the borrower location is orthogonal to the error term: $E(\epsilon_{i,b,t}|\text{Overconfidence}_{\text{Math}}, X) = 0$. In support for this assumption, we first show that geographic characteristics (X_p) are not correlated with pupils' overconfidence, other than a weakly significant negative correlation with trust, which is actually fully captured by the South dummy (Panel A of Table 2).[23] 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

[22] The share of overconfident students in Mathematics correlates well with two alternative measures of overconfidence: (i) the share of students reporting that they find Italian easier than their classmates; (ii) those who think they are good in Mathematics even though they have a score below the median score across pupils in Italy. All our results hold if we use these alternative measures of pupils' overconfidence.

[23] Households in the South of Italy are characterized by low levels of social capital and trust in institutions (Guiso et al., 2004).

using the share of population with college degrees and for social capital using the measure from Guiso et al. (2004), i.e. voter turnout at the referendum in Italy between 1946 and 1989 (available for 92 provinces). As shown in Panel B of Table 2, pupils in the South are generally more overconfident in their ability in Math than their fellow students in the Center who in turn are more overconfident than those in the North. Because of this underlying correlation, overconfidence is also 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.

We present in Figure 2 the residuals of pupils' overconfidence after controlling for all the local geographic factors that we also include in the estimation of equation (1). This is the variation in pupils' overconfidence, net of local socio-economic factors, that we actually exploit in our regressions. Overall, we conclude that, while local overconfidence is not orthogonal to local socio-economic characteristics, the residual variation after controlling for these factors (in particular the macro-area dummies) is plausibly exogenous.

Movers. Admittedly, a potential concern with the strategy outlined above is that some other unobserved province characteristics might be driving our results. To address this concern, we exploit the presence of "movers" in our sample, i.e. managers of firms located in a different province from the one they were born in (as in Guiso et al., 2004, 2021). Movers are affected not only by the overconfidence of the place where they currently live, but also by the overconfidence of the place they grew up in. This effect is present if there is an inherited component in overconfidence, or if people's expectations are affected by their past experiences, determined by what people live through and observe around them early in their lifetime, which in turn depends on location (Malmendier and Nagel, 2011).

More specifically, we obtain managers' province of birth from their social security number available from the Italian Chamber of Commerce ($Infocamere$). This sample is available from 2005. We then restrict the sample to firms whose top managers were born in a different province from the one the firm headquarter is.[24] Since 70% of managers and entrepreneurs in Italy work in the same province they were born in (Baltruinate et al., 2019), focusing on movers reduces the sample by more than two thirds, but it allows to include province-year fixed effects, controlling for any other unobserved time-varying local shocks. Formally, we run the following regression:

$$Y_{i,b,t} = \beta \text{Overconfidence (Orig)}_{\text{Math},s} + \gamma' X_k + \lambda_{j,t} + \lambda_{p,t} + \lambda_{b,t} + \epsilon_{i,b,t} \tag{2}$$

where Overconfidence $(\text{Orig})_{\text{Math},s}$ is the share of overconfident pupils in province s 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_k, such as the risk and social preference variables from Falk et al. (2018) for the region of origin of the manager, plus other demographic characteristics such as age and gender. Compared to equation (1) we include a province-year fixed-effect $\lambda_{p,t}$ (instead of the macro-area year fixed effect $\lambda_{k,t}$) to control more tightly for any unobserved local shock, beyond industry and bank-year fixed-effects ($\lambda_{j,t}$ and $\lambda_{b,t}$).

Most firms with movers (75%) are located in the North of the country, consistent with the fact that internal migration is mostly a South to North phenomenon. We acknowledge that moving is not random and one may worry that overconfident managers match with riskier firms. However, we do not find that the overconfident movers join ex-ante riskier firms compared to movers from low overconfidence areas. In the years before the overconfident manager moves to the company, the company does not have a worse credit score, higher volatility of sales or lower profits than firms who hire less overconfident managers (Table A.4 in the Online Appendix).

[24] We focus only on the firms' senior managers, namely the CEO and other top executives (e.g. CFO or Directors of sales). When a firm has more than one manager who moved from her province of birth (15% of the observations in the "movers" sample), we take an average of the overconfidence of the province of birth of all the movers (up to four managers).

5 Overconfidence, forecast errors and credit outcomes

5.1 Pupils' overconfidence and firm forecast errors

Before turning to credit outcomes, we show that there is indeed a robust and significant relationship between pupils' local overconfidence and the likelihood that local managers issue overly-optimistic forecasts on future sales growth in INVIND, in excess of 10 percentage points of realized growth ($\mathbb{1}(FE > 0.1)$). Figure 3 visually suggests pupils' overconfidence in Mathematics or Italian has a positive correlation with positive forecast errors on firms' future sales across Italian provinces.

Next, we test whether the simple correlation is robust to the inclusion of a series of control variables, akin to a first-stage regression, and present the results in Panel A of Table 3. We start by including only firm characteristics plus year fixed-effects, and find a statistically significant relationship between pupils' overconfidence and firms' forecast errors on their future sales.

[INSERT TABLE 3 HERE]

We control for local geographic factors in column (2). Reassuringly, the coefficient on local overconfidence remains similar as we control for these other local characteristics and the R^2 does not change, suggesting that observable local factors do not affect overconfidence (Oster, 2019). The coefficient remains significant when we further absorb South-year, North-year and industry-year fixed-effects in columns (3)-(4) to allow for time-varying shocks in different areas and sectors, including the 2007-08 financial crisis (Barone et al., 2018); and credit score-year fixed effects in column (5). The effect is economically large: a borrower located in a province with the highest level of overconfidence (0.78) is 6.6 percentage points (0.6×0.11) more likely to make a large positive forecast error compared to a borrower in the least overconfident province (0.67). This is a 27% (0.066/0.24) increase relative to the mean of $\mathbb{1}(FE > 0.1)$.

Finally, in column (6) we estimate the specification presented in equation (2) in the restricted mover sample. Even though the sample is reduced by more than two-thirds, in this specification we can include province-year fixed-effects based on the location of the firm to tightly absorb any other local time-varying shock. The coefficient on the overconfidence of the province of birth of the manager is positive, significant and remarkably close to the effect in the baseline sample. Overall, these results confirm that there is a strong and robust relationship between pupils' and borrowers' overconfidence across areas.

Overconfidence vs. optimism. The share of pupils who claim they find Mathematics easier than their classmates may also be related to a general tendency of being optimistic about all future outcomes, even for those outside the managers' control. To assess this, we look separately at firm expectations about their own future performance and aggregate economic outcomes from SIGE (as in Coibion et al., 2019). The results are presented in Table A.5 in the Online Appendix. Pupils' self-declared ability in Math at the local level is positively and significantly correlated with firms' expectations about their own future business conditions (Panel A), but not about the overall state of the economy (Panel B). This finding is consistent with the fact that our measure of overconfidence captures managers' tendency to overestimate their own ability ("better than average" effect), rather than a generalized upward bias in beliefs. This is important to distinguish our measure of overconfidence from dispositional optimism about the future state of the economy (Puri and Robinson, 2007).

Overconfidence vs. miscalibration. Finally, we perform several additional robustness tests which we report in Table A.6 in the Online Appendix. First, we do not find that our measure of overconfidence is correlated with forecast precision, as measured by the difference between the upper and lower bound interval of sales forecasts, which some firms report in INVIND (Panel A). This allows us to distinguish overconfidence from miscalibration (Ben-David et al., 2013). Second, our results are robust if we directly regress overconfidence on the forecast errors, rather than the dummy for a large positive forecast error (Panel B). Third, our results are robust if we use several alternative measures of local overconfidence from the INVALSI survey (Panel C): using the share of pupils who find Italian easier than their classmates or those who think they are good in Math but score below the median.

5.2 Credit outcomes

We now estimate the effects of overconfidence on credit outcomes using equations (1) and (2). Results are presented in Table 4.

[INSERT TABLE 4 HERE]

In Panel A we first show that borrower overconfidence is priced in loan terms. Borrowers located in an area with the highest level of overconfidence pay interest rates on their loans that are 20% higher relative to the mean ($10.6 \times 0.11/5.8$) compared to borrowers located in the least overconfident areas. Quantitatively, the estimated effect of overconfidence is similar to that of credit risk: a high-risk firm (credit score$\geq$7) pays a 14% higher loan rate compared to a non-risky firm. The results are not capturing a "South" effect, as we are controlling for South (and North) times year fixed-effects and a host of other geographic factors (including the efficiency of law enforcement, and local attitudes towards trust). Similarly, the coefficient of interest remains stable when we include industry times year fixed effects in column (2), firm characteristics in column (3) and credit score-year fixed-effects in column (4). The estimated effect is smaller (7%) but still positive and significant when we restrict the sample to movers in column (5).[25] These results are consistent with our model where sophisticated banks are able to observe borrowers' overconfidence and price it in their loan terms.

Second, in Panel B we find that overconfident borrowers, when they obtain credit, have a higher share of their loans backed by collateral compared to other borrowers. The results are also economically significant: borrowers located or born in the most overconfident area have 29% ($0.45 \times 0.11/0.17$) higher share of collateralized loans relative to borrowers located or born in the least overconfident area (we exclude overdrafts from the analysis as these loans are not secured by collateral). These effects are stable as we saturate the regression with fixed-effects and controls.

[25] The results also hold across loan types (overdrafts, credit lines backed by receivables and term loans) see Table A.7 in the Online Appendix.

Finally, we show overconfidence affects the probability of receiving bank credit in Panel C. In order to do this, we exploit the richness of the Italian credit register that contains information on loan applications and acceptances at the firm-bank-year level.[26] Loan applicants located in overconfident areas have lower acceptance rates than similar firms in other areas. A borrower from the most overconfident area has an acceptance rate that is 11% ($-0.25 \times 0.11/0.25$) lower compared to a borrower from the least overconfident area (the point estimates are similar but not significant in the movers sample in this case).[27] Quantitatively, the estimated effect of overconfidence are 3.5 times higher than those credit risk: high-risk firms face acceptance rates that are only 3% lower than non-risky firms. Thus, overconfident borrowers are more likely to be denied credit, and when they receive it, they have to pay higher loan rates and have to pledge more collateral.

Bank overconfidence? If local entrepreneurs are overconfident, what about local loan officers? In this subsection, we address the concern that our results could be confounded by differences in bank behavior across areas with low versus high overconfidence.

First of all, we argue that there are no clear theoretical reasons as to why bank overconfidence should bias our estimates in a particular direction. Conceptually, overconfident loan officers have biased beliefs about their own ability to screen borrowers and hence they are ex-ante equally likely to reject or accept applications from local firms.

Second, we include bank-year fixed-effects in all specifications. This ensures that bank-time specific variation, including bank overconfidence, does not affect our results. Moreover, we repeat the analysis within the subsample of large banks, for which lending decisions tend to follow uniform rules across geographical areas (Berger et al., 2005; Liberti et al., 2016). We present the results in Table A.9 in the Online Appendix, excluding first the very small

[26]Loan applications data come from requests about borrowers' credit history (*richiesta di prima informazione*) that banks file with the credit register when a firm asks for a loan. We restrict the sample to loan applications from first-time borrowers that apply to more than one bank in a year in order to use firm-year fixed-effects in the estimation.

[27]In Online Appendix Table A.8, we look at loan demand (Panel A) and find that overconfident borrowers are not more likely to apply for credit than other firms. In Panel B, we look at amount of credit granted, and confirm that overconfident borrowers are less likely to obtain credit.

cooperative banks that serve customers within a province, then small-medium banks with assets below €21 billion and finally excluding all but the largest banks with assets above €100 billion. Reassuringly, our estimates are virtually unchanged in all cases, suggesting that potential differences in the behavior of local branches within the same bank do not have a material impact on our findings.

Finally, we highlight that the potential confounding impact of bank overconfidence is also addressed by the tests that we run on the sample of managers who moved, where we include fixed effects for the province of the firm headquarters. To the extent that firms borrow from banks located near their headquarters (Degryse and Ongena, 2005), these fixed effects also absorb any potential differences in local loan officers' behavior across Italian areas.

6 Credit Supply and the Collateral Channel

In this section, we provide empirical evidence on the effects of collateral requirements on lending to overconfident borrowers.

According to our model in Section 2, collateral requirements (χ) on the firms' assets that can be seized upon default can be interpreted as an asset-specific or bank-specific recovery value. Empirically, we capture the former using industry differences in tangibility and the latter using a unique Bank of Italy survey on banks. An advantage of measuring collateral at bank-level instead of industry-level is that in this case the interaction term between borrower overconfidence and collateral is not absorbed by firm-year fixed-effects, i.e. we can exploit variation in acceptance rates across banks for firms that file multiple loan applications within a year (Jiménez et al., 2014). Under some conditions, this allows to identify differences in the supply of credit across banks (Khwaja and Mian, 2008). For our purposes, it is also important to note that firm-year fixed-effects absorb any confounding factor, including local shocks, that may affect overconfidence.

Although we do not directly observe bank recovery value on collateral, we exploit a unique bank survey run by Bank of Italy in 2006, where banks were asked to report details on their lending practices including their reliance on collateral requirements when lending to first-time borrowers (question B3 in the survey, reproduced in the Online Appendix Figure A.2). Figure 1 shows substantial dispersion among banks in the importance they assign to collateral in their lending decisions. We confirm in the data that higher reported reliance on collateral in the survey is positively correlated with the share of guaranteed credit at the bank level throughout the sample period (Table A.1 in the Online Appendix). Thus, collateral-based banks as per the survey definition actually lend more on a collateralized basis and are specialized in the recovery value of collateral. Formally, we estimate the following equation:

$$\begin{aligned} Accept_{i,b,t} = {} & \beta_1 \text{Overconfidence}_{\text{Math},p} + \beta_2 \text{Overconfidence}_{\text{Math},p} \times Collateral_b + \\ & \lambda Log(Dist_{i,b}) + \mu_{i,t} + \mu_{b,t} + \epsilon_{i,b,t} \end{aligned} \tag{3}$$

where $Accept_{i,b,t}$ is a dummy equal to one if the loan application filed by firm i with bank b, with which it had no previous lending relationship (i.e., firm i is a potential first-time borrower for bank b) at time t is accepted. $Collateral_b$ is the importance of collateral that the bank attaches to real or personal guarantees when lending to first-time borrowers, ranging from 1 (least important) to 6 (most important). As mentioned above, in robustness tests we also use the fraction of tangible over total assets at the sector level as an alternative measure of collateral importance and find similar results. $\mu_{i,t}$ and $\mu_{b,t}$ are firm-year and bank-year fixed-effects. Finally, we also include the (log of) bilateral geographic distance between the bank headquarter and the firm headquarter, to control for a "gravity effect" in lending (Degryse and Ongena, 2005).

[INSERT TABLE 5 HERE]

We present the results in Table 5. The coefficient on the interaction term between $\text{Overconfidence}_{\text{Math},p}$ and Collateral_b is positive and statistically significant, indicating that collateral-based banks are more likely to accept loan applications from overconfident borrowers. Importantly, since in column (2) we include firm-year fixed-effects (Khwaja and Mian, 2008), the coefficient of interest is identified off variation between banks with different collateral requirements that review a loan application from the same firm at the same time. Quantitatively, a one standard deviation increase in overconfidence (+0.025) for a bank that thinks that collateral is the most important factor in lending to first-time borrowers ($Collateral_b = 6$) leads to an increase in the acceptance rate by 16% (0.265*6*0.025/0.25) compared to virtually no effect for a bank that values collateral the least ($Collateral_b = 1$). That is, collateral-based banks are significantly less likely to deny credit to overconfident borrowers. We then progressively saturate the regression with bank-year fixed-effects in column (3), thus absorbing bank-time unobserved heterogeneity (such as lending policies or bank overconfidence): the coefficient of the interaction term between overconfidence and reliance on collateral remains positive. In what follows, we provide several robustness tests showing that the coefficient on the interaction term remains positive and significant.

Bank characteristics. The results may be driven by banks' characteristics which are correlated with collateral requirements. To address this concern, we augment our baseline specification interacting pupils' overconfidence with three key banks' characteristics: size, regulatory capital and the quality of loan portfolios. As shown in column (4) of Table 5, these additional interaction terms are all statistically insignificant while the coefficient on the interaction between $\text{Overconfidence}_{\text{Math},p}$ and Collateral_b remains virtually unchanged.[28]

Credit risk. We then ask whether the results on collateral requirements are specific to corporate overconfidence per se, or reflect a more general pattern of banks' behavior towards riskier firms in general.[29] For this, in column (5) of Table 5 we include the interaction of Collateral_b and the dummy for high credit risk. We find that the coefficient is not significant,

[28] We also explore whether other survey factors drive bank lending decisions in Table A.10 in the Online Appendix. We find that banks that rely less on quantitative and more on qualitative information are more likely to lend to overconfident borrowers. Importantly though the effect of collateral remains positive and significant, suggesting that the effect of collateral requirements works beyond the use of hard or soft information.

[29] Manove et al. (2001) and Goel et al. (2014) show theoretically that banks' incentives to screen borrowers are lower the higher the reliance on collateral, consistent with the fact that asset-based lending relies on the assessment of the value of collateral, not of the borrower and its cash-flows (Berger and Udell, 2006)

i.e. collateral-based banks are not more likely to lend to observably riskier firms in general, and the coefficient on the main interaction of interest between collateral and overconfidence remains unchanged. Similarly, we include an exhaustive set of Collateral$_b$ $\times$ credit score dummies $\times$ year fixed-effects in column (6), and find that the coefficient on the interaction between collateral and overconfidence is unchanged. Thus reliance on collateral induces banks to lend more to overconfident firms, not to ex-ante riskier firms in general.

Movers. We further restrict the sample to movers in column (7) of Table 5 and find that the coefficient on the interaction term between overconfidence of the province of birth of the manager and reliance on collateral remains positive and significant. The results confirm that within a given firm, bank and year, banks that rely more on collateral are less likely to deny credit to loan applicants born in overconfident areas.

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 collateral and present the results in Online Appendix Table A.11. Specifically, we run the same specification as in equation 3 except that the variable Collateral$_b$ is now the average ratio of tangible to total assets ($Tangible/TotalAssets$) at the 2-digit sector-year level. While the coefficient on the pupils' overconfidence is negative and significant, the interaction term with the asset tangibility ratio is positive and larger in magnitude than the stand-alone coefficient. Quantitatively, for a one standard deviation increase in local overconfidence, firms in hypothetical industries with no tangible fixed assets face a lower acceptance rate of about 5% compared to the mean, whereas those in industries with all assets being tangible have an acceptance rate which is 5% higher.

Intensive margin. The results in Table 5 show that overconfident borrower are more likely to receive credit from high-collateral banks. But do they also get larger loans? To test this, we replace the dependent variable with a variable equal to the (log of) the amount of credit granted when the application is accepted. The results are presented in Table A.12 in the Online Appendix. We find that overconfident borrowers are granted larger loans by banks that value collateral more. Thus, overconfident borrowers are more likely to scale up their operations, including investment, when they borrow from collateral-based banks.

Robustness to other geographic factors. It is possible that geographical differences in economic development or the quality of local institutions, drive the correlation between local overconfidence and collateral. To rule this out we augment our baseline specification with the interaction of collateral requirements and other geographical characteristics, namely GDP per capita, a South dummy, the duration of bankruptcy proceedings, and local preferences towards trust etc, in order to address the concern that our estimates could instead simply reflect that collateral requirements improve firms' access to credit in poorer areas or areas in which contract enforcement is weak. We present the results in Online Appendix Table A.13. Reassuringly, in all specifications, the coefficient on the interaction term remains positive and statistically significant.

7 Corporate Investment and Default

Our findings so far have shown that bank heterogeneity in the reliance on collateral requirements matters for the allocation of credit to overconfident borrowers. A natural follow-up question is whether credit supply decisions affect corporate outcomes. Since collateral-based banks are more inclined to lend to overconfident firms, access to bank credit may further increase the (over-)investment made by overconfident managers, and their probability to default.[30] In this section, we aim to shed light on these questions.

Investment. To establish the presence of this channel, we compute the firm-level investment rate, defined as the change in fixed assets over total fixed assets in the previous year, and we test whether overconfident borrowers have a higher investment intensity if they receive a larger share of credit from collateral-based banks. Results are presented in Table 6.

[INSERT TABLE 6 HERE]

[30] This stands in contrast to the prediction of standard models with asymmetric information where borrowers with high credit risk, which are aware of their low-quality, are disciplined by collateral requirements.

We confirm in column (1) that corporate investment is higher for overconfident borrowers, after controlling for firm characteristics and an exhaustive set of fixed-effects. This finding echoes previous studies showing that overconfident managers invest more than others (Malmendier and Tate, 2005; Ben-David et al., 2013).[31] The estimates imply that moving from the province with the lowest to the highest level of pupils' overconfidence is associated with a 1.98 percentage points (0.18×0.11) higher investment rate. This is a large economic effect, which represents an 18% increase compared to the average investment rate in the sample. We find a similar effect for the movers sample (column 2).

We then explore whether the sensitivity of investment to overconfidence depends on whom overconfident borrowers borrow from. In particular, we are interested in testing whether collateral-based banks are fueling the investment made by overconfident managers through their lending decisions. We construct the importance of collateral-based lending by taking the firm-year average of bank level collateral survey ($Collateral_{f,t} = \sum_b w_{bft-1} \times Collateral_b$), where the weights ($w_{bft-1}$) are the share of credit from each bank b lending to firm f. We find in column (3) that the higher sensitivity of investment to overconfidence is entirely driven by these banks: only overconfident borrowers who obtain credit from collateral-based banks have higher investment rates compared to non-overconfident borrowers. This is a novel result in the literature and indicates that the real effect of managerial overconfidence on investment is amplified by the collateral lending channel.

The higher investment sensitivity of overconfident borrowers is not due to credit risk: in columns (4-5) we include the interaction of Collateral$_{f,t}$ with the the dummy for high risk borrowers (credit score$\geq$7). The coefficient on the interaction of interest between collateral and overconfidence remains unchanged. Moreover, we find that high risk firms that borrow from high-collateral banks invest 5% less than others. The negative coefficient shows that high-risk

[31] Overconfident managers may be risky because they innovate more (Galasso and Simcoe, 2011; Hirshleifer et al., 2012). We match the firms in our sample to the Patent Statistical database (PATSTAT) of the European Patent Office, which contains patent filings at the firm year level. We find that more than 99% of the firms in our sample do not have patents, which is not surprising given it is mostly composed of private SMEs. We conclude that innovation is unlikely to play a role in our setting.

borrowers are disciplined by collateral requirements, consistent with standard theoretical predictions (Boot and Thakor, 1994; Thakor and Udell, 1991).

Default. In this section, we 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 credit register. A bad loan is a type of non-performing loan (NPL) where the borrower is insolvent or in substantially similar circumstances.

First, we investigate the effect of overconfidence on firm-level 1-year default probability, regressing the share of overconfident pupils on a dummy equal to one if the firm credit exposure is classified as bad debt by the bank in year $t+1$. The results are presented in Table 7, columns (1-2).

[INSERT TABLE 7 HERE]

Borrowers from the most overconfident areas are 92% more likely to default ($0.19 \times 0.11/0.025$) than those from the least overconfident areas. This is a large effect, but to assess the impact of higher default rates on bank balance sheets we have to take into account the evidence from Section 5.2 where we show that overconfident borrowers pay higher rates and have a higher share of loans backed by collateral. Interestingly, a simple back-of-the-envelope calculation suggests that the higher interest rate charged to overconfident borrowers is enough to compensate banks for the extra-default risk. In fact, if the loan rate is equal to the probability of default (PD) times the loss-given-default (LGD), considering that average recovery rates on bad loans to non-financial firms in Italy between 2006 and 2017 are 36%, the loan rate should be 13% (0.21×0.64) higher for overconfident borrowers. This estimate is remarkably close to the estimated coefficient (10.6) in Table 4 column (4).

Second, we ask whether our estimates are quantitatively large enough to explain the distribution of bad loans in the cross-section of banks. In order to do this, we aggregate the amount of bad loans at the province or bank-province level and look at whether overconfident provinces, and banks with high reliance on collateral, have a higher volume of bad loans. We confirm in Table 7 columns (3-7) that default rates are sensitive to local pupils' overconfidence in specifications aggregated at the province-level, and that the higher incidence of aggregate default in overconfident areas is driven by collateral-based banks, that end up with more non-performing loans in overconfident areas as a fraction of their overall loan portfolio.

Finally, we use these estimates to compute a back-of-the-envelope aggregate amount in yearly overconfidence-induced default that would have been avoided if banks were not relying on collateral-based lending, exploiting cross-sectional differences in banks' reliance on collateral, and using the group of banks with the lowest reliance on collateral ($Collateral_b = 1$) as a counterfactual group.[32] We compute it using the following formula:

$$\Delta BadLoans = \sum_b \sum_p \beta \times Overconfidence_{Math,p} \times (Collateral_b - 1) \times Credit_b \tag{4}$$

where $\beta = 0.01$ is the estimate on the interaction term $Overconfidence_{Math,p} \times Collateral_b$ in column (7) of Table 7, $Collateral_b$ is the collateral score of bank b, $Overconfidence_{Math,p}$ is pupil overconfidence in province p, and $Credit_b$ is total loan portfolio size in euros of bank b. For the year 2017 (the last year of our sample), we find that collateral-based lending lead to an increase in overconfidence-induced bad loans of around €10 billion. This represents 8% of the aggregate stock of bad loans for non-financial corporate lending in Italy in 2017. It is important to 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 37% of secured 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 overconfidence on banks' balance sheet in the aggregate.

Taken together, these findings provide new evidence on how bank lending affects the economic impact of overconfidence and shed light on how collateral requirements may decrease

[32] To the extent that banks with the lowest reliance on collateral still use collateral requirements in their lending decisions, this number can be seen as a lower-bound estimate for the amount in yearly overconfidence-induced default that would have been avoided if banks were not relying on collateral-based lending.

lending efficiency when borrowers have biased beliefs.

8 Conclusion

In this paper, we study how banks lend to borrowers who are overconfident in the quality of their projects. Since overconfidence is endogenous, our identification strategy relies on variation in pupils' overconfidence across areas in Italy. We provide evidence that pupils' overconfidence is persistent, is not correlated with local measures of economic development and trust, and predicts the likelihood that local managers issue over-optimistic sales growth forecasts.

Our main contribution is to document that banks are more likely to deny credit to borrowers born in overconfident areas, but only when collateral requirements are low. Importantly, the collateral lending channel amplifies the real effects associated with overconfidence: overconfident borrowers invest more than others only when they borrow from collateral-based banks. In turn, overconfident borrowers default more ex-post, with aggregate implications on the distribution of non-performing loans in the cross-section of banks. Overall, our findings shed light on the instrumental role of banks' credit supply decisions in shaping how managers' overconfidence affect economic outcomes.

References

Adam, Tim, Valentin Burg, Tobias Scheinert, and Daniel Streitz, "Managerial biases and debt contract design: the case of syndicated loans," *Management Science*, 2020, *66* (1), 1–501.

Baltruinate, Audinga, Elisa Brodi, and Sauro Mocetti, "Ownership structure and governance of Italian companies: new evidence and effects on performance," 2019.

Barone, Guglielmo, Guido DeBlasio, and Sauro Mocetti, "The real effects of credit crunch in the great recession: Evidence from Italian provinces," *Regional Science and Urban Economics*, 2018, *70*, 352–359.

Barrero, Jose Maria, "The micro and macro of managerial beliefs," *Journal of Financial Economics*, 2022, *143* (2), 640–667.

Ben-David, Itzhak, John R. Graham, and Campbell R. Harvey, "Managerial miscalibration," *The Quarterly Journal of Economics*, 2013, *128* (4), 1547–1584.

Berger, Allen N. and Gregory F. Udell, "Collateral, loan quality and bank risk," *Journal of Monetary Economics*, 1990, *25* (1), 21–42.

_ **and** _ , "A more complete conceptual framework for SME finance," *Journal of Banking & Finance*, November 2006, *30* (11), 2945–2966.

Berger, Allen N, W Scott Frame, and Vasso Ioannidou, "Tests of ex ante versus ex post theories of collateral using private and public information," *Journal of Financial Economics*, 2011, *100* (1), 85–97.

Berger, Allen, Nathan Miller, Mitchell Petersen, Raghuram Rajan, and Jeremy Stein, "Does function follow organizational form? Evidence from the lending practices of large and small banks," *Journal of Financial Economics*, 2005, *76*, 237–269.

Besanko, David and Anjan V Thakor, "Collateral and rationing: sorting equilibria in monopolistic and competitive credit markets," *International economic review*, 1987, *28* (3), 671–689.

Bester, Helmut, "Screening vs. rationing in credit markets with imperfect information," *American Economic Review*, 1985, *75* (4), 850–55.

Boot, Arnoud WA and Anjan V Thakor, "Moral hazard and secured lending in an infinitely repeated credit market game," *International economic review*, 1994, *35* (4), 899–920.

Bordalo, Pedro, Nicola Gennaioli, and Andrei Shleifer, "Diagnostic expectations and credit cycles," *The Journal of Finance*, 2018, *73* (1), 199–227.

Brick, Ivan E and Darius Palia, "Evidence of jointness in the terms of relationship lending," *Journal of Financial Intermediation*, 2007, *16* (3), 452–476.

Cain, Carol, Mei Feng, and Douglas Skinner, "Does earnings guidance affect market returns? The nature and information content of aggregate earnings guidance," *Journal of Accounting and Economics*, 2007, *44*, 36–63.

Carlana, Michela, "Implicit stereotypes: evidence from teachers' gender bias," *The Quarterly Journal of Economics*, 2019, *134* (3), 1163–1224.

Carvalho, Daniel, Janet Gao, and Pengfei Ma, "Loan spreads and credit cycles: the role of lenders' personal economic experiences," 2021. Working Paper.

Coibion, Olivier, Yuriy Gorodnichenko, and Tiziano Ropele, "Inflation expectations and firm decisions: new causal evidence," *The Quarterly Journal of Economics*, 2019, *135* (1), 165–219.

Coval, Joshua and Anjan Thakor, "Financial intermediation as a beliefs-bridge between optimists and pessimists," *Journal of Financial Economics*, 2005, *75*, 535–569.

de Meza, David, "Overlending?," *The Economic Journal*, 2002, *112* (477), F17–F31.

_ **and Clive Southey**, "The borrower's curse: optimism, finance and entrepreneurship," *The Economic Journal*, 1996, *106* (435), 375–386.

Degryse, Hans and Steven Ongena, "Distance, lending relationships, and competition," *Journal of Finance*, 2005, *60* (1), 231–266.

D'Acunto, Francesco, Marcel Prokopczuk, and Michael Weber, "Historical antisemitism, ethnic specialization, and financial development," *The Review of Economic Studies*, 2019, *86* (3), 1170–1206.

Fahlenbrach, Rüdiger, Robert Prilmeier, and René M. Stulz, "This time is the same: using bank performance in 1998 to explain bank performance during the recent financial crisis," *Journal of Finance*, 2012, *67* (6), 2139–2185.

Falk, Armin, Anke Becker, Thomas Dohmen, Benjamin Enke, David Huffman, and Uwe Sunde, "Global evidence on economic preferences," *The Quarterly Journal of Economics*, 2018, *133* (4), 1645–1692.

Fecht, Falko and Regina Opaleva, "Managerial overconfidence and access to funding: do banks help managers to avoid investment mistakes?," 2019.

Galasso, Alberto and Timothy S. Simcoe, "CEO overconfidence and innovation," *Management Science*, 2011, *57* (8), 1469–1484.

Gervais, Simon, James B. Heaton, and Terrance Odean, "Overconfidence, compensation contracts, and capital budgeting," *Journal of Finance*, 2011, *66* (5), 1735–1777.

Goel, Anand and Anjan Thakor, "Overconfidence, CEO selection and corporate governance," *Journal of Finance*, 2008, *63* (5), 2737–2784.

Goel, Anand M., Fenghua Song, and Anjan V. Thakor, "Correlated leverage and its ramifications," *Journal of Financial Intermediation*, 2014, *23* (4), 471–503.

Greenwood, Robin and Samuel G. Hanson, "Issuer quality and corporate bond returns," *The Review of Financial Studies*, 2013, *26* (6), 1483–1525.

Guiso, Luigi and Giuseppe Parigi, "Investment and demand uncertainty," *The Quarterly Journal of Economics*, 02 1999, *114* (1), 185–227.

_ , Luigi Pistaferri, and Fabiano Schivardi, "Learning entrepreneurship from other entrepreneurs?," *Journal of Labor Economics*, 2021, *39* (1), 135–191.

_ , Paola Sapienza, and Luigi Zingales, "The role of social capital in financial development," *American Economic Review*, 2004, *94* (3), 526–556.

_ , _ , and _ , "Long-term persistence," *Journal of the European Economic Association*, 2016, *14* (6), 1401–1436.

Hackbarth, Dirk, "Managerial traits and capital structure decisions," *Journal of Financial and Quantitative Analysis*, 2008, *43* (4), 843–881.

Hacker, Douglas J, Linda Bol, Dianne D Horgan, and Ernest A Rakow, "Test prediction and performance in a classroom context," *Journal of Educational Psychology*, 2000, *92*, 160–170.

Heaton, James B., "Managerial optimism and corporate finance," *Financial Management*, 2002, *31*, 33–45.

Hirshleifer, David, Angie Low, and Siew Hong Teoh, "Are overconfident CEOs better innovators?," *Journal of Finance*, 2012, *67* (4), 1457–1498.

Inderst, Roman and Holger M. Mueller, "Informed lending and security design," *Journal of Finance*, 2006, *61* (5), 2137–2162.

Ioannidou, Vasso, Nicola Pavanini, and Yushi Peng, "Collateral and asymmetric information in lending markets," *Journal of Financial Economics*, 2022, *144* (1), 93–121.

Jiménez, Gabriel, Steven Ongena, José-Luis Peydró, and Jesús Saurina, "Hazardous times for monetary policy: What do 23 million loans say about the impact of monetary policy on credit risk-taking?," *Econometrica*, 2014, *82* (2), 463–505.

Jiménez, Gabriel, Vicente Salas, and Jesus Saurina, "Determinants of collateral," *Journal of Financial Economics*, 2006, *81* (2), 255–281.

Khwaja, Asim and Atif Mian, "Tracing the impact of bank liquidity shocks: evidence from an emerging market," *The American Economic Review*, 2008, *98* (4), 1413–1442.

Kose, John, Anthony W Lynch, and Manju Puri, "Credit ratings, collateral, and loan characteristics: Implications for yield," *The Journal of Business*, 2003, *76* (3), 371–409.

Landier, Augustin and David Thesmar, "Financial contracting with optimistic entrepreneurs," *The Review of Financial Studies*, 2008, *22* (1), 117–150.

Langer, Ellen J., "The illusion of control," *Journal of Personality and Social Psychology*, 1975, *32* (2), 311–328.

Liberti, José María, Amit Seru, and Vikrant Vig, "Information, credit, and organization," Working Paper 2016.

Lin, Chih-Yung, Yehning Chen, Po-Hsin Ho, and Ju-Fang Yen, "CEO overconfidence and bank loan contracting," *Journal of Corporate Finance*, 2020, *64*, 101637.

Ma, Yueran, Teodora Paligorova, and José-Luis Peydró, "Expectations and bank lending," 2020.

_ , Tiziano Ropele, David Sraer, and David Thesmar, "A quantitative analysis of distortions in managerial forecasts," 2019. Working Paper.

Malmendier, Ulrike and Geoffrey Tate, "CEO overconfidence and corporate investment," *Journal of Finance*, 2005, *60* (6), 2661–2700.

_ and _ , "Who makes acquisitions? CEO overconfidence and the market's reaction," *Journal of Financial Economics*, 2008, *89*, 20–43.

_ and Stefan Nagel, "Depression babies: do macroeconomic experiences affect risk taking?," *The Quarterly Journal of Economics*, 2011, *126* (1), 373–416.

_ , Geoffrey Tate, and Jon Yan, "Overconfidence and early-life experiences: the effect of managerial traits on corporate financial policies," *Journal of Finance*, 2011, *66* (6), 1687–1733.

_ , Vincenzo Pezone, and Hui Zheng, "Managerial duties and managerial biases," *Management Science*, 2022.

Manove, Michael, A. Jorge Padilla, and Marco Pagano, "Collateral versus project screening: a model of lazy banks," *RAND Journal of Economics*, 2001, *32* (4), 726–744.

_ and Jorge Padilla, "Banking (conservatively) with optimists," *The RAND Journal of Economics*, 1999, *30* (2), 324–350.

Michalopoulos, Stelios and Melanie Meng Xue, "Folklore," *The Quarterly Journal of Economics*, 2021, *136* (4), 1993–2046.

Moore, Don A and Paul J Healy, "The trouble with overconfidence.," *Psychological review*, 2008, *115* (2), 502.

Oskamp, Stuart, "Overconfidence in case-study judgments," *Journal of Consulting Psychology*, 1965, *29* (3), 261–265.

Oster, Emily, "Unobservable selection and coefficient stability: theory and evidence," *Journal of Business & Economic Statistics*, 2019, *37* (2), 187–204.

Otto, Clemens, "CEO optimism and incentive compensation," *Journal of Financial Economics*, 2014, *114*, 366–404.

Puri, Manju and David T. Robinson, "Optimism and economic choice," *Journal of Financial Economics*, 2007, *86* (1), 71 – 99.

Sandroni, Alvaro and Francesco Squintani, "Overconfidence, insurance, and paternalism," *American Economic Review*, 2007, *97* (5), 1994–2004.

Thakor, Anjan V and Gregory F Udell, "Secured lending and default risk: equilibrium analysis, policy implications and empirical results," *The Economic Journal*, 1991, *101* (406), 458–472.

Figure 1: **Bank Heterogeneity in Collateral Requirements**

This histogram reports the frequency of the relative importance of collateral requirements in lending decisions to first-time borrowers across banks in the 2006 Bank Organizational Survey.

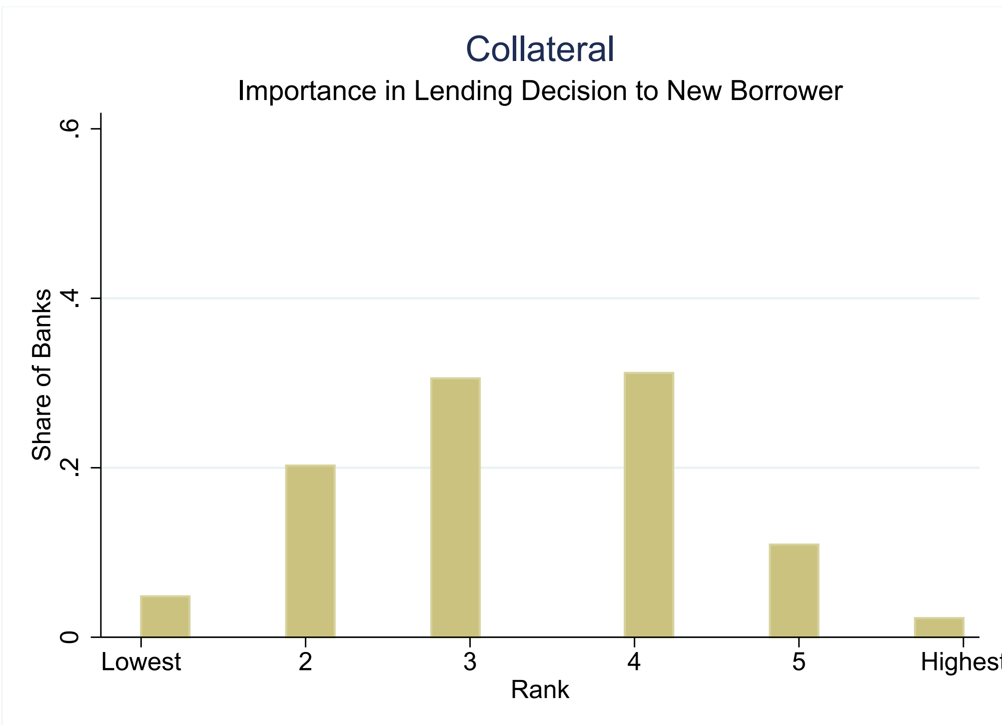


Figure 2: **Overconfidence in Mathematics**

This map reports the residuals from a regression of students' overconfidence, i.e. the share of students 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 in 2001-2017, the length of bankruptcy proceedings in 2006, the region-averages from the preference survey in Falk et al. (2018) and a dummy for the South.

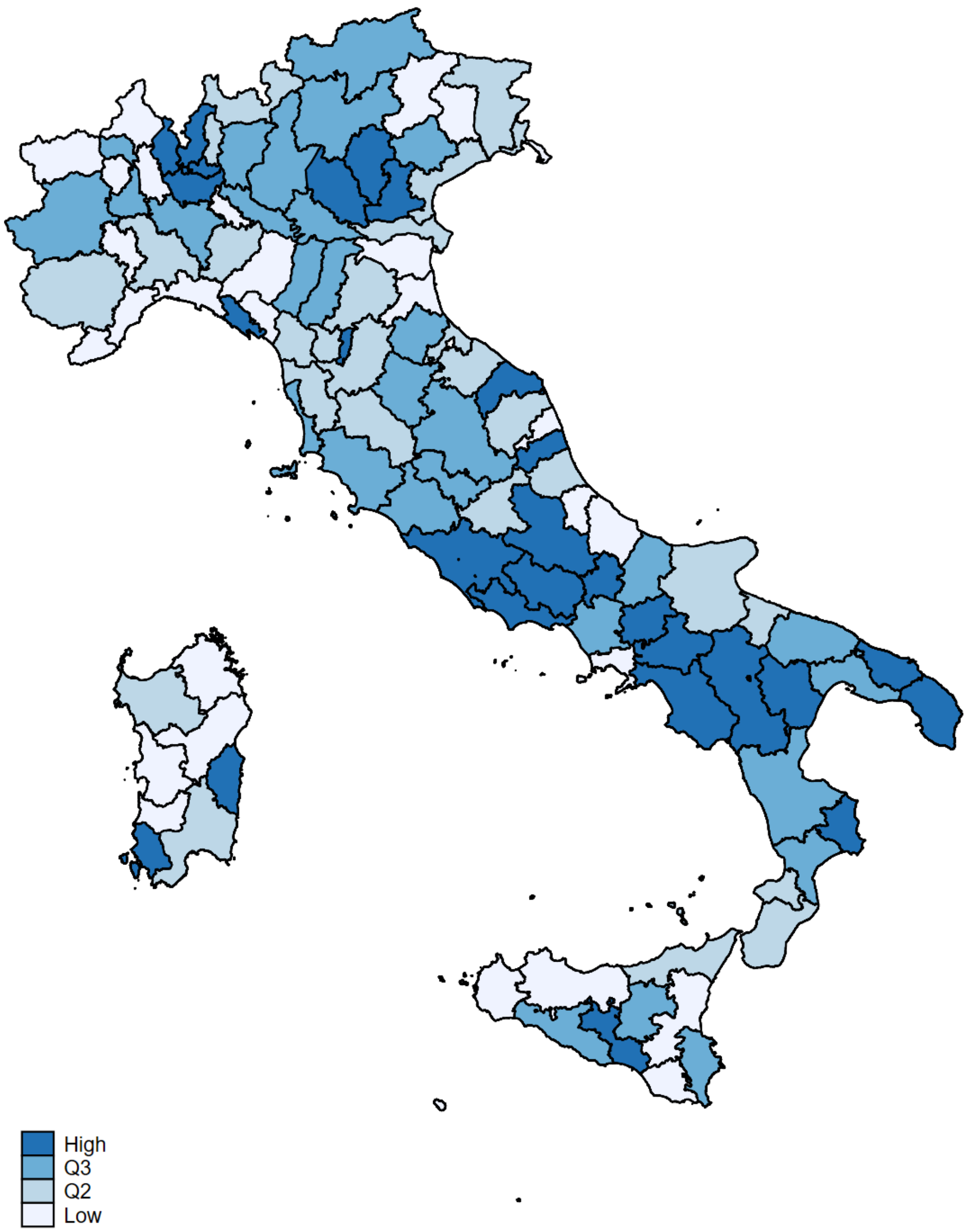
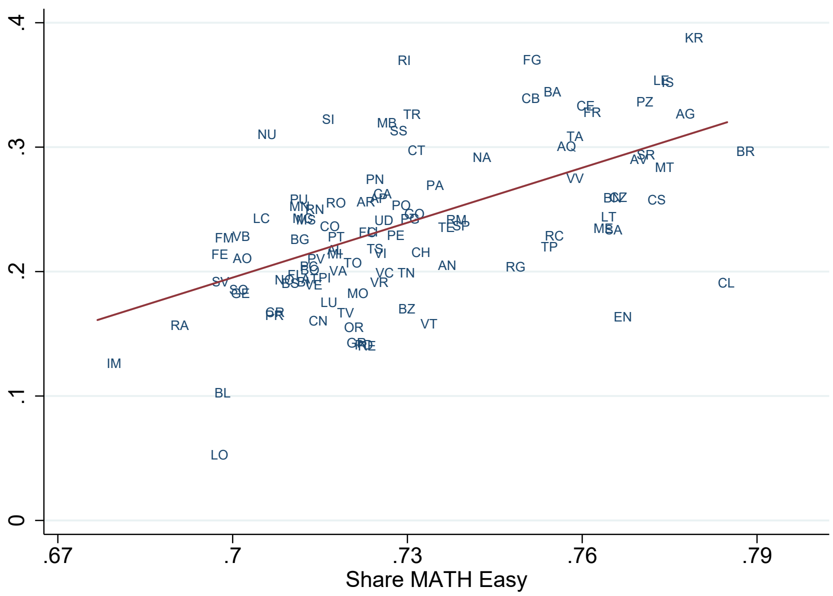


Figure 3: **Probability of Issuing Overconfident Forecast**

This figure contains a scatter plot of firms' likelihood of issuing "over-optimistic" forecasts at the province level, i.e. the province-average of $\mathbb{1}(FE_{t+1|t} > 0.1)$, on pupils' overconfidence in Math (Panel A) and Italian (Panel B).

Panel A. Overconfidence$_{\text{Math}}$



Panel B. Overconfidence$_{\text{Italian}}$

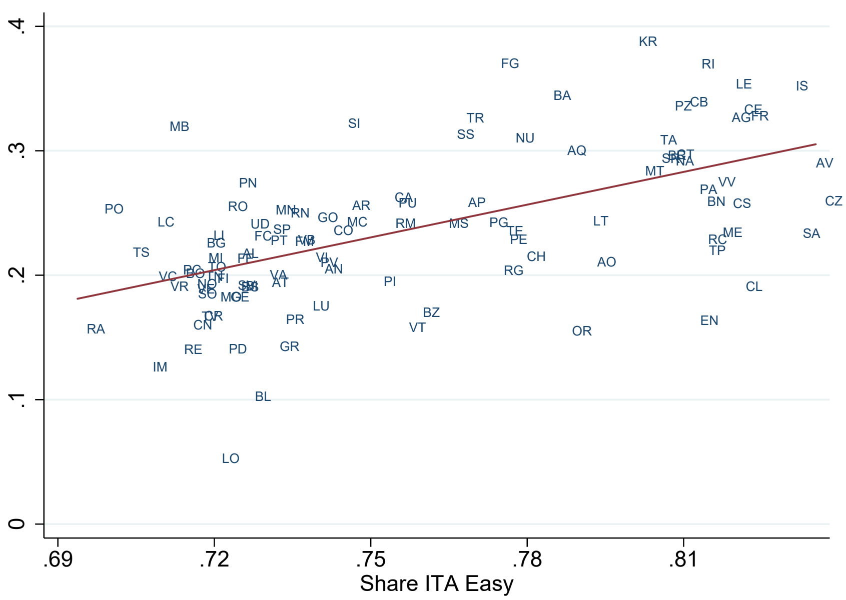


Table 1: **Summary Statistics**

This table presents the summary statistics for our data at the firm-year level (2001-2017) for the INVIND sample which consists of about 5,000 firms (Panel A); at the province level from INVALSI (2009-2013 average) and other province characteristics (2001-2017 average 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 2001-2017 at firm-bank level (Panel C); firm characteristics at firm-year level (Panel D); at the bank level for the Organizational Survey in 2006 (Panel E). All firm-year and firm-bank-year variables have been winsorized at the 1^{st}-99^{th} percentiles (except for the investment rate, which has been winsorized at the 5^{th}-95^{th} percentile).

	(1)	(2)	(3)	(4)	(5)	(6)
	Obs.	Mean	SD	P1	P50	P99
Panel A. INVIND survey, firm-year level						
$FE_{i,t+1\|t} = (F_t(Sales_{i,t+1}) - Sales_{i,t+1})/Sales_{i,t}$	42437	0.017	0.181	-0.615	0.012	0.643
$FE_{i,t+1\|t} = LogF_t(Sales_{i,t+1}) - LogSales_{i,t+1}$	42421	0.041	0.225	-0.590	0.019	1.052
$\mathbb{1}(FE_{i,t+1\|t} < -0.1)$	42437	0.174	0.379	0.000	0.000	1.000
$\mathbb{1}(FE_{i,t+1\|t} > 0.1)$	42437	0.237	0.425	0.000	0.000	1.000
Interval Forecast Sales Growth (Max-Min)$_{i,t+1\|t}$	14489	0.082	0.079	0.000	0.060	0.428
Sales Growth (t,t+1)	42437	0.022	0.223	-0.581	0.016	0.759
Sales Growth Volatility	42437	0.155	0.170	0.008	0.103	0.957
Firm age (years)	42437	29.489	17.724	4.000	26.000	92.000
Firm Assets (€million)	42437	100.68	497.51	1.24	18.067	1554.8
EBITDA/Assets	42437	0.080	0.086	-0.174	0.074	0.356
Credit Score	42437	4.316	1.840	1.000	4.000	8.000
$\mathbb{1}$(Bad Debt in t+1)	42437	0.029	0.169	0.000	0.000	1.000
Panel B. INVALSI, Province or Region characteristics						
Overconfidence$_{\text{Math}}$	110	0.727	0.025	0.677	0.722	0.782
Overconfidence$_{\text{Italian}}$	110	0.756	0.040	0.697	0.744	0.833
GDP/Pop (€)	110	21478	5724	12679	21521	34776
Law Inefficiency (days)	110	4148	2134	1259	3632	11558
Patience	19	0.103	0.189	-0.350	0.110	0.514
Risk Taking	19	-0.109	0.159	-0.379	-0.099	0.245
Positive Reciprocity	19	0.185	0.224	-0.102	0.192	0.789
Negative Reciprocity	19	0.301	0.292	-0.400	0.351	0.810
Altruism	19	0.352	0.231	-0.047	0.286	0.825
Trust	19	-0.087	0.165	-0.546	-0.075	0.154
Panel C. Credit Register, firm-bank-year level						
Loan Rate in %	5805124	5.852	2.598	0.791	6.684	12.902
Collateralized Credit/Total	5371366	0.177	0.356	0.000	0.237	1.000
$\mathbb{1}$(Loan Application Accepted)	848131	0.249	0.432	0.000	0.000	1.000
=Ln(Credit) if Loan Application Accepted	848131	3.122	5.449	0.000	0.000	14.915
$\mathbb{1}$(Loan Application Made)	6450953	0.494	0.500	0.000	0.000	1.000
Panel D. Borrower characteristics, firm-year level						
Investment Rate ($\Delta FixAssets_t/FixAssets_{t-1}$)	3075965	0.111	0.452	-0.401	-0.017	1.54
Default rate	3117343	0.025	0.155	0.000	0.000	1.000
HighRisk	3117343	0.208	0.383	0.000	0.000	1.000
Firm Age (years)	3117343	17.269	12.730	3.000	14.000	60.000
Log(Firm Assets$_{t-1}$)	3117343	7.346	1.326	4.762	7.197	11.281
Sales Growth (t,t+1)	3117343	0.080	0.471	-0.790	0.018	3.024
Sales Growth Volatility	3117343	0.379	0.700	0.011	0.172	4.423
Panel E. Organizational Survey in 2006, bank level						
Qualitative Info	311	3.563	1.403	1.000	4.000	6.000
Collateral	311	3.701	1.123	1.000	4.000	6.000
Quantitative Methods	311	5.039	1.628	1.000	6.000	6.000
Balance Sheet	311	1.830	1.124	1.000	1.000	6.000
Credit Register	311	2.293	1.131	1.000	2.000	6.000
Personal Knowledge	311	4.553	1.160	1.000	5.000	6.000

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 the following: 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 in 2001-2017; 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). *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

	Panel A. Region-level Overconfidence$_{\text{Math}}$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
South								0.030***
								(0.007)
Patience	-0.005						0.000	-0.018
	(0.030)						(0.048)	(0.031)
Risk Taking		0.017					0.031	0.028
		(0.035)					(0.043)	(0.027)
Positive Reciprocity			0.024				0.052	0.033
			(0.024)				(0.037)	(0.023)
Negative Reciprocity				-0.005			-0.041	-0.022
				(0.019)			(0.031)	(0.020)
Altruism					-0.009		-0.017	-0.012
					(0.024)		(0.037)	(0.023)
Trust						-0.058*	-0.092*	-0.053
						(0.031)	(0.047)	(0.031)
Observations	19	19	19	19	19	19	19	19
R^2	0.002	0.013	0.052	0.003	0.008	0.162	0.442	0.796

	Panel B. Province-level Overconfidence$_{\text{Math}}$					
	(1)	(2)	(3)	(4)	(5)	(6)
South	0.027***					0.010
	(0.005)					(0.010)
North	-0.011***					-0.007
	(0.004)					(0.005)
Log(GDP/Pop)		-0.060***				-0.021
		(0.008)				(0.014)
Law Inefficiency			0.029***			-0.001
			(0.004)			(0.006)
Share College				-0.121		0.054
				(0.117)		(0.106)
Social Capital (Guiso et al., 2004)					-0.204***	-0.079
					(0.018)	(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 $\mathbb{1}(FE_{i,t+1|t} > 0.1)$, a dummy equal to one if the firm forecast error on future sales growth exceeds 10 percentage points, 0 otherwise. $\text{Overconfidence}_{\text{Math}}$ ($\text{Overconfidence}_{\text{Math}}$ (Orig)) is the share of pupils who say that they find Mathematics easier than their classmates in the province where the firm is located (manager is born). 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. Manager characteristics (Orig) are the same geographic controls calculated for the province or region (Falk et al., 2018) of birth of the manager, including a female dummy indicator and the (log of) manager's age. Area-year fixed-effects are North×Year and South×Year fixed-effects (where the omitted category is Center). Firm controls include: current realized and past growth rate of sales, sales growth volatility in the past three years, lagged EBITDA/assets, the (log of) firm age and total assets; the Cerved Altman Z-score index, ranging from 1 (lowest risk) to 9 (highest risk). 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)	Movers (6)
	$\mathbb{1}(FE_{i,t+1\|t} > 0.1)$					
$\text{Overconfidence}_{\text{Math}}$	1.014***	0.864***	0.815***	0.606***	0.606***	
	(0.147)	(0.217)	(0.227)	(0.215)	(0.212)	
$\text{Overconfidence}_{\text{Math}}$ (Orig)						0.678**
						(0.287)
Province-Year FE	N	N	N	N	N	Y
Firm Controls	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	-	-	-	-
Geographic Controls	N	Y	Y	Y	Y	-
Area-Year FE	N	N	Y	Y	Y	-
Industry-Year FE	N	N	N	Y	Y	Y
$\mathbb{1}$(Credit Score)-Year FE	N	N	N	N	Y	Y
Manager characteristics (Orig)	N	N	N	N	N	Y
Observations	42437	42437	42437	42437	42437	11893
R^2	0.246	0.247	0.247	0.281	0.284	0.345

Table 4: **Overconfidence and Credit Outcomes**

The unit of observation is a firm-bank-year. In Panel A the dependent variable is the average interest rate across loan types, in Panel B the share of credit backed by collateral at the firm-year level and in Panel C a dummy equal to one if the loan application is accepted, 0 otherwise. $\text{Overconfidence}_{\text{Math}}$ ($\text{Overconfidence}_{\text{Math}}$ (Orig)) is the share of pupils who say that they find Mathematics easier than their classmates in the province where the firm is located (manager is born). Geographic controls include: log GDP per capita, the length of bankruptcy proceedings, the region-averages from the preference survey in Falk et al. (2018). HighRisk is a dummy equal to one if the Cerved Altman Z-score index, ranging from 1 (lowest risk) to 9 (highest risk), is above 7. Area-year fixed-effects are North×Year and South×Year fixed-effects (where the omitted category is Center). Other firm controls include: current realized and past growth rate of sales, sales growth volatility in the past three years, EBITDA/assets, the (log of) firm age and total assets. 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)	Movers (5)
	Panel A. Average Loan Rate (%)				
$\text{Overconfidence}_{\text{Math}}$	11.160***	12.090***	10.834***	10.653***	
	(2.239)	(2.606)	(2.054)	(2.019)	
HighRisk			0.847***		
			(0.020)		
$\text{Overconfidence}_{\text{Math}}$ (Orig)					3.620***
					(0.397)
Observations	5805124	5805124	5805124	5805124	1326952
R^2	0.224	0.210	0.307	0.329	0.337
	Panel B. Collateralized Credit/Total				
$\text{Overconfidence}_{\text{Math}}$	0.381	0.503**	0.457**	0.452**	
	(0.261)	(0.248)	(0.191)	(0.191)	
HighRisk			0.015***		
			(0.002)		
$\text{Overconfidence}_{\text{Math}}$ (Orig)					0.394***
					(0.062)
Observations	5371366	5371366	5371366	5371366	1066044
R^2	0.089	0.092	0.160	0.161	0.188
	Panel C. $\mathbb{1}$(Loan Application Accepted)				
$\text{Overconfidence}_{\text{Math}}$	-0.192*	-0.196*	-0.231**	-0.253**	
	(0.107)	(0.108)	(0.115)	(0.112)	
HighRisk			-0.008***		
			(0.002)		
$\text{Overconfidence}_{\text{Math}}$ (Orig)					-0.369
					(1.054)
Observations	848131	848131	848131	848131	173218
R^2	0.037	0.044	0.050	0.056	0.0798
Province-Year FE	N	N	N	N	Y
Geographic Controls	Y	Y	Y	Y	-
Bank-Year FE	Y	Y	Y	Y	Y
Area-Year FE	Y	Y	Y	Y	-
Industry-Year FE	N	Y	Y	Y	Y
Other Firm Controls	N	N	Y	Y	Y
$\mathbb{1}$(Credit Score)-Year FE	N	N	N	Y	Y

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

The unit of observation is a firm-bank-year. The dependent variable is a dummy equal to one if the loan application is accepted, 0 otherwise. $\text{Overconfidence}_{\text{Math}}$ ($\text{Overconfidence}_{\text{Math}}$ (Orig)) is the share of pupils who say that they find Mathematics easier than their classmates in the province where the firm is located (manager is born). Collateral_b is the answer to the bank delegation survey regarding the following question: "when a borrower comes to your bank for the first time, how important is: i) guarantees, either real or personal". The answers are reported as a ranking from 1 to 6, with higher values representing higher importance. Geographic controls include: log GDP per capita, the length of bankruptcy proceedings, the region-averages from the preference survey in Falk et al. (2018). Capital is the bank regulatory capital ratio, NPL/Assets is share of non-performing loans over total assets and Log(Assets) is the natural logarithm of bank total assets. Log(Dist) is the geographical distance between the province of the bank headquarter and that of the firm headquarter. Standard errors presented in parentheses are two-way clustered at the bank and province level. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	Movers (7)
	$\mathbb{1}$(Loan Application Accepted)						
$\text{Overconfidence}_{\text{Math}} \times \text{Collateral}_b$	0.262*	0.265***	0.368***	0.405***	0.403***	0.405***	
	(0.136)	(0.094)	(0.102)	(0.108)	(0.107)	(0.105)	
$\text{Overconfidence}_{\text{Math}}(\text{Orig}) \times \text{Collateral}_b$							0.314***
							(0.087)
Collateral_b	-0.190*	-0.189***					
	(0.105)	(0.070)					
$\text{Overconfidence}_{\text{Math}}$	-0.967**						
	(0.392)						
$\text{HighRisk} \times \text{Collateral}_b$					-0.001		
					(0.003)		
$\text{Overconfidence}_{\text{Math}} \times \text{Capital}$				0.048	0.047	0.052	
				(0.044)	(0.042)	(0.044)	
$\text{Overconfidence}_{\text{Math}} \times \text{NPL/Assets}$				0.040	0.040	0.041	
				(0.031)	(0.031)	(0.031)	
$\text{Overconfidence}_{\text{Math}} \times \text{Log(Assets)}$				0.056	0.056	0.056	
				(0.048)	(0.048)	(0.048)	
Log(Dist)	-0.013***	-0.012***	-0.008***	-0.008***	-0.008***	-0.008***	
	(0.003)	(0.003)	(0.001)	(0.001)	(0.002)	(0.002)	
Area-Year FE	Y	-	-	-	-	-	-
Geographic controls	Y	-	-	-	-	-	-
Firm-Year FE	N	Y	Y	Y	Y	Y	Y
Bank-Year FE	N	N	Y	Y	Y	Y	Y
Collateral-$\mathbb{1}$(Credit Score)-Year FE	N	N	N	N	N	Y	Y
Overconfidence(Orig)×BankCharact.	N	N	N	N	N	N	Y
Observations	848131	848131	848131	848131	848131	848131	173094
R^2	0.007	0.473	0.491	0.491	0.491	0.492	0.500

Table 6: **Overconfidence and Investment**

The unit of observation is a firm-year. The dependent variable is the firm investment rate, i.e. the change in fixed-assets over lagged fixed assets. Overconfidence$_{\text{Math}}$ (Overconfidence$_{\text{Math}}$ (Orig)) is the share of pupils who say that they find Mathematics easier than their classmates in the province where the firm is located (manager is born). Collateral$_{f,t}$ is the firm-year weighted average of the answer to the bank delegation survey regarding collateral importance, where the weights are the share of loans by bank b lending to firm f in year t. Geographic controls include: log GDP per capita, the length of bankruptcy proceedings, the region-averages from the preference survey in Falk et al. (2018). Area-year fixed-effects are North×Year and South×Year fixed-effects (where the omitted category is Center). Firm controls include: current realized and past growth rate of sales, sales growth volatility in the past three years, lagged EBITDA/assets, the (log of) firm age and total assets, the Cerved Altman Z-score index, ranging from 1 (low risk) to 9 (high risk). Standard errors presented in parentheses are clustered at the province level. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

		Movers			Movers
	(1)	(2)	(3)	(4)	(5)
	Investment Rate				
Overconfidence$_{\text{Math}}$	0.179***		0.003	0.002	
	(0.049)		(0.067)	(0.066)	
Overconfidence$_{\text{Math}}$ (Orig)		0.124***			-0.061
		(0.043)			(0.067)
Collateral$_{f,t}$			-0.099***	-0.098***	-0.085***
			(0.010)	(0.010)	(0.018)
Overconfidence MATH × Collateral$_{f,t}$			0.116***	0.117***	
			(0.014)	(0.014)	
HighRisk × Collateral$_{f,t}$				-0.005***	-0.004***
				(0.001)	(0.001)
Overconfidence MATH (Orig)× Collateral$_{f,t}$					0.097***
					(0.025)
Province-Year FE	N	Y	N	N	Y
Area-Year FE	Y	Y	Y	Y	Y
Other Firm Controls	Y	Y	Y	Y	Y
Industry-Year FE	Y	Y	Y	Y	Y
$\mathbb{1}$(Credit Score)-Year FE	Y	Y	N	Y	Y
Observations	3084806	592354	3084806	3084806	592354
R^2	0.039	0.046	0.040	0.040	0.047

Table 7: **Overconfidence 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 columns (1-2), the share of bad loans over total credit at the province (columns 3-4) or bank-province (columns 5-7) in each year. $\text{Overconfidence}_{\text{Math}}$ ($\text{Overconfidence}_{\text{Math}}$ (Orig)) is the share of pupils who say that they find Mathematics easier than their classmates in the province where the firm is located (manager is born). Collateral_b is the answer to the bank delegation survey regarding the following question: "when a borrower comes to your bank for the first time, how important is: i) guarantees, either real or personal". The answers are reported as a ranking from 1 to 6, we standardize them so that higher values mean higher importance of that factor. Geographic controls include: log GDP per capita, the length of bankruptcy proceedings, the region-averages from the preference survey in Falk et al. (2018). Standard errors presented in parentheses are clustered at the province level. Regressions are weighted by loan volume in each province. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

	(1)	Movers (2)	(3)	(4)	(5)	(6)	(7)
	Default Rate						
	Firm		Province		Bank-Province		
$\text{Overconfidence}_{\text{Math}}$	0.216***		0.192**	0.218**	-0.076		
	(0.041)		(0.076)	(0.104)	(0.049)		
$\text{Overconfidence}_{\text{Math}}$ (Orig)		0.175***					
		(0.037)					
$\text{Overconfidence}_{\text{Math}} \times \text{Collateral}_b$					0.035**	0.034**	0.010*
					(0.017)	(0.015)	(0.006)
Collateral_b					-0.024**	-0.024**	
					(0.012)	(0.011)	
Area-Year FE	Y	Y	Y	Y	Y	Y	Y
Geographic Controls	Y	Y	N	Y	Y	-	-
$\mathbb{1}$(Credit Score)-Year FE	Y	Y	N	N	-	-	-
Firm Controls	Y	Y	-	-	-	-	-
Province FE	N	N	N	N	N	Y	Y
Bank-Year FE	-	-	-	-	N	N	Y
Observations	3117343	598985	1616	1616	64923	64939	64923
R^2	0.040	0.047	0.219	0.277	0.046	0.086	0.758

Online Appendix

Lending to Overconfident Borrowers

This Online Appendix includes a series of additional Figures and Tables.

A Appendix Figures and Tables

Figure A.1: **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 they ask students "What do you think about Mathematics/Italian" ("Che cosa pensi della Matematica/Italiano"), eliciting their beliefs on their own ability in Italian and Mathematics respectively , with a simple yes ("si") 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

INVALSI

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.

		Sì	*No*
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	☐	☐

Figure A.2: **Bank of Italy Survey on the Lending Practices of Italian Banks**

This figure presents question B3 of the survey about banks' lending practices run by the Bank of Italy in 2006. More than 300 banks participated in the survey, accounting for around 85% per cent of the overall Italian banking system's lending to firms. We merge each bank in the survey with the credit registry data using unique banks' identifiers. The question asks banks to rank the following six factors from the most important to the least important when assessing the decision of whether or not to grant credit to a new borrower: "Quantitive methods only" (*Metodo esclusivamente statistico-quantitativi*), "Balance sheet information" (*Dati di bilancio delle imprese*), "Credit score" (*Informazioni dalle relazioni creditizie in essere con il sistema (fonte Centrale rischi e/o altri Credit Bureau) o da fonti pubbliche (Centrale allarme interbancaria, Bollettino dei protesti, ecc.)*, "Collateral requirements" (*Disponibilita di garanzie personali e/o reali concesse da confidi*), "Qualitative information" (*Informazioni qualitative*), "Other information based on personal acquaintance" (*Altre valutazioni basate sulla conoscenza diretta*). The question is asked separately when new borrowers are SMEs (first column) or large firms (second column). We use the information for when new borrowers are SMEs. The results (and survey answers) are virtually indentical when using information in column 2.

B3 – Con riferimento alla concessione **di prestiti a imprese non finanziarie che si rivolgono alla vostra banca per la prima volta**, **ordinare** per importanza i fattori valutativi utilizzati nel decidere sulla concessione del credito **assegnando 1 al più importante, 2 al successivo e così via**. Non è possibile assegnare a voci diverse lo stesso valore. Nel caso in cui il fattore valutativo non è applicabile apporre "NA".

	PMI	Grandi imprese
Metodi esclusivamente statistico-quantitativi		
Dati di bilancio delle imprese (1)		
Informazioni dalle relazioni creditizie in essere con il sistema (fonte Centrale rischi e/o altri *Credit Bureau*) o da fonti pubbliche (Centrale allarme interbancaria, Bollettino dei protesti, ecc.) (1)		
Disponibilità di garanzie personali e/o reali e/o concesse da confidi		
Informazioni qualitative (*struttura organizzativa dell'impresa, caratteristiche del progetto da finanziare ecc.*) (1)		
Altre valutazioni basate sulla conoscenza diretta		
Altro (specificare		

Figure A.3: **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 between 2001 and 2017, separately for the subsample of observations with negative and positive forecast errors. Each dot represents an equal size bin of firm forecast errors (100 bins). The vertical dash line indicates a forecast error of zero.

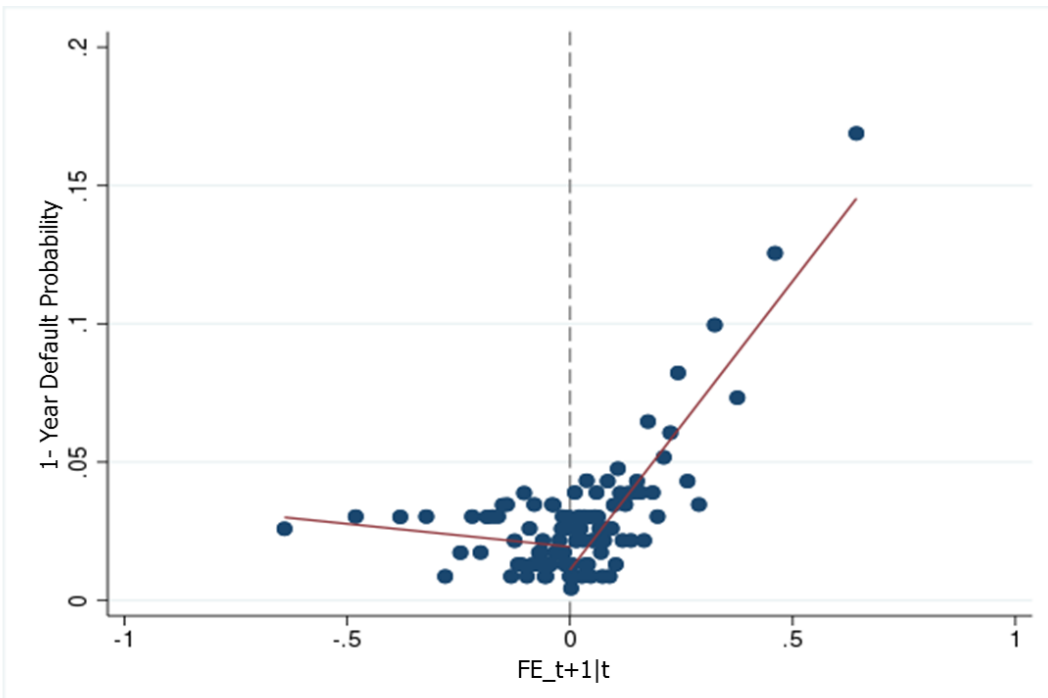


Table A.1: **Bank Collateral Survey and Collateral Usage**

The dependent variable is the share of collateralized (term) credit at the bank level between 2001 and 2017. Collateral_b is the answer to the 2006 bank delegation survey regarding the following question: "when a borrower comes to your bank for the first time, how important is: i) guarantees, either real or personal". The answers are reported as a ranking from 1 to 6, we standardize them so that higher values mean higher importance of that factor. Capital is the bank regulatory capital ratio, NPL/Assets is share of non-performing loans over total assets and Log(Assets) is the natural logarithm of bank total assets. All bank characteristics are one-period lagged. Standard errors presented in parentheses are White-robust. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)
	Share of Collateralized Credit		
Collateral_b	0.834**	0.814***	0.771***
	(0.346)	(0.271)	(0.264)
Capital			0.522***
			(0.109)
NPL/Assets			0.132
			(0.092)
Log(Assets)			-2.549***
			(0.173)
Year FE	N	Y	Y
Observations	2583	2583	2583
R^2	0.023	0.433	0.48

Table A.2: **Firm Forecast Errors and Default**

The dependent variable is the 1-year probability of default (=1 if a loan of the firm becomes bad debt in year t+1) at the firm-year level. $\mathbb{1}(FE_{i,t+1|t} > 0.1)$ is a dummy equal to one if the firm forecast error on future sales growth from INVIND survey exceeds 10 percentage points, 0 otherwise. Credit Score is Cerved Altman Z-score index, ranging from 1 (lowest risk) to 9 (highest risk). Standard errors presented in parentheses are clustered at the firm level. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)
	$\mathbb{1}$(Bad Debt in t+1)			
$\mathbb{1}(FE_{i,t+1\|t} > 0.1)$	0.031***	0.031***	0.013***	0.013***
	(0.003)	(0.003)	(0.003)	(0.003)
Sales Growth (t,t+1)			-0.043***	-0.033***
			(0.007)	(0.007)
Sales Growth (t-1,t)			-0.032***	-0.022***
			(0.006)	(0.006)
Sales Growth Volatility			0.034***	0.025**
			(0.010)	(0.010)
EBITDA/Assets			-0.050**	-0.052***
			(0.019)	(0.019)
Log(Firm Age)			0.011***	0.011***
			(0.003)	(0.003)
Log(Assets)			0.003	0.002
			(0.002)	(0.002)
Credit Score			0.012***	
			(0.001)	
Year FE	Y	-	-	-
Industry-Year FE	-	Y	Y	Y
$\mathbb{1}$(Credit Score)-Year FE	-	-	-	Y
Observations	42437	42437	42437	42437
R^2	0.006	0.028	0.049	0.074

Table A.3: **Overconfidence: Persistence and Alternative Measures**

The unit of observation is a province. The dependent variable is the share of pupils who say they are good in Math in the 2012-2013 INVALSI wave in column 1, and across all INVALSI waves (2009-2010; 2011-2012; 2012-2013) in columns 2-3. $\text{Overconfidence}_{\text{Math}}$ 2009 is the share of students who find Mathematics easier than their classmates in 2009; $\text{Overconfidence}_{\text{Italian}}$ is the share of students who find Italian easier than their classmates averaged across 2009-2012; "MATH good but below median" is the share of students who think they are good in Mathematics but obtain a below the median INVALSI score in Mathematics. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)
	$\text{Overconfidence}_{\text{Math}}$ 2012	$\text{Overconfidence}_{\text{Math}}$ 2009-2012	
$\text{Overconfidence}_{\text{Math}}$ 2009	0.711***		
	(0.054)		
$\text{Overconfidence}_{\text{Italian}}$		0.484***	
		(0.037)	
Math good but below median			0.863***
			(0.079)
Observations	110	110	110
R^2	0.634	0.607	0.527

Table A.4: **Do Overconfident Managers Match With Riskier Firms?**

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 where the firm headquarter is located. The dependent variable is the firm credit score in columns 1-2; sales growth volatility in the past three years in columns 3-4; net profits over assets in columns 5-6, measured in the year before the mover joins the firm. Overconfidence$_{\text{Math}}$ (Orig) 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 (Orig) include averages for the province of birth in: log GDP per capita, the length of bankruptcy proceedings, the region-averages from the preference survey in Falk et al. (2018); a female dummy indicator and the (log of) managers' age. 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 characteristic in the year before mover joins:					
	Credit Score		Vol(Sales Growth)		Profits/Assets	
Overconfidence$_{\text{Math}}$ (Orig)	0.857	0.649	-0.138	-0.046	-0.009	-0.004
	(0.903)	(0.760)	(0.274)	(0.047)	(0.029)	(0.025)
Other manager charact.	Y	Y	Y	Y	Y	Y
Province-Year FE	Y	Y	Y	Y	Y	Y
Area-Year FE	Y	Y	Y	Y	Y	Y
Industry-Year FE	Y	Y	Y	Y	Y	Y
Firm Controls	N	Y	N	Y	N	Y
Observations	196081	196081	196148	196148	195811	195811
R^2	0.087	0.132	0.097	0.723	0.092	0.141

Table A.5: **Pupils' Overconfidence and Future Business Conditions (SIGE Survey)**

The dependent variable is an answer in the SIGE survey at firm-year level. In Panel A and columns 1-2 of Panel C the question is about the firm own business condition in the next 3 months, from 1 ("Worse") to 3 ("Better"). In Panel B and columns 3-4 of Panel C the question is about the probability that the Italian economy will improve in the next 3 months, from 1 (0% probability) to 6 (100% probability). $\text{Overconfidence}_{\text{Math}}$ is the province-level share of pupils who say that they find Mathematics easier than their classmates (INVALSI test). Geographic controls include: log GDP per capita, the length of bankruptcy proceedings, a South dummy and the region-averages from the preference survey in Falk et al. (2018). Area-year fixed-effects are North×Year and South×Year fixed-effects (where the omitted category is Center). Firm controls include: current realized and past growth rate of sales, sales growth volatility in the past three years, lagged EBITDA/assets, the (log of) firm age and total assets, the Cerved Altman Z-score index, ranging from 1 (lowest risk) to 9 (highest risk). 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)
	Panel A. Firm Own Business Condition Improves Next 3M			
$\text{Overconfidence}_{\text{Math}}$	1.915*	2.337**	2.337**	2.380**
	(1.001)	(0.960)	(0.960)	(0.947)
Observations	4627	4627	4627	4627
R^2	0.118	0.223	0.223	0.236
	Panel B. Probability Economy Improves Next 3M			
$\text{Overconfidence}_{\text{Math}}$	-0.629	0.084	0.084	0.419
	(1.719)	(1.472)	(1.472)	(1.457)
Geographic Controls	Y	Y	Y	Y
Firm Controls	Y	Y	Y	Y
Year FE	Y	-	-	-
Area-Year FE	N	Y	Y	Y
Industry-Year FE	-	Y	Y	Y
$\mathbb{1}$(Credit Score)-Year FE	-	-	-	Y
Observations	4627	4627	4627	4627
R^2	0.115	0.217	0.217	0.230
	Panel C. INVIND - SIGE Matched Sample			
	Firm Own Business Condition Improves Next 3M		Italian Economy Improves Next 3M	
$\text{FE}_{t+1\|t}$	0.417**	0.457**	0.271	0.208
	(0.163)	(0.178)	(0.283)	(0.295)
Geographic Controls	Y	Y	Y	Y
Firm Controls	Y	Y	Y	Y
Industry-Year FE	Y	Y	Y	Y
$\mathbb{1}$(Credit Score)-Year FE	-	Y	-	Y
Observations	1076	1076	1076	1076
R^2	0.382	0.409	0.380	0.426

Table A.6: **Overconfidence and Firm Forecast Errors: Robustness**

The unit of observation is a firm-year pair. The dependent variable is the difference between the maximum and minimum forecast on sales growth next year in Panel A, the forecast error in Panel B, and a dummy equal to one if the forecast error on sales growth exceeds 10% in Panel C. In Panel C we use different measures of overconfidence: $\text{Overconfidence}_{\text{Italian}}$ is the share of students who find Italian easier than their classmates averaged across 2009-2012, "Math good but below median" is the share of students who think they are good in Mathematics but obtain a below the median INVALSI score in Mathematics. 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)
	Panel A. Forecast Interval_i (Upper - Lower Bound)				
$\text{Overconfidence}_{\text{Math}}$	-0.053	0.057	0.019	-0.016	-0.019
	(0.088)	(0.134)	(0.136)	(0.132)	(0.130)
Observations	14489	14489	14489	14424	14423
R^2	0.061	0.065	0.070	0.136	0.147
	Panel B. $(F_t(Sales_{i,t+1}) - Sales_{i,t+1})/Sales_{i,t}$				
$\text{Overconfidence}_{\text{Math}}$	0.275***	0.234***	0.233***	0.198***	0.196***
	(0.054)	(0.080)	(0.079)	(0.073)	(0.073)
Firm Controls	Y	Y	Y	Y	Y
Year FE	Y	Y	-	-	-
Area-Year FE	N	N	Y	Y	Y
Industry-Year FE	N	N	N	Y	Y
Credit Score-Year FE	N	N	N	N	Y
Observations	42437	42437	42437	42437	42437
R^2	0.564	0.565	0.565	0.582	0.585
	Panel C. $\mathbb{1}(FE_{i,t+1}) > 0.1$				
$\text{Overconfidence}_{\text{Italian}}$	0.472***	0.462***			
	(0.141)	(0.139)			
Math good but below median			0.512***	0.495***	
			(0.215)	(0.214)	
Firm Controls	Y	Y	Y	Y	
Area-Year FE	Y	Y	Y	Y	
Industry-Year FE	Y	Y	Y	Y	
Credit Score-Year FE	N	Y	N	Y	
Observations	42437	42437	42437	42437	
R^2	0.280	0.284	0.280	0.284	

Table A.7: **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. $\text{Overconfidence}_{\text{Math}}$ ($\text{Overconfidence}_{\text{Math}}$ (Orig)) is the share of pupils who say that they find Mathematics easier than their classmates in the province where the firm is located (manager is born). Geographic controls include: log GDP per capita, the length of bankruptcy proceedings, the region-averages from the preference survey in Falk et al. (2018). HighRisk is a dummy equal to one if the Cerved Altman Z-score index, ranging from 1 (lowest risk) to 9 (highest risk), is above 7. Area-year fixed-effects are North$\times$Year and South$\times$Year fixed-effects (where the omitted category is Center). Other firm controls include: current realized and past growth rate of sales, sales growth volatility in the past three years, EBITDA/assets, the (log of) firm age and total assets. 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)	Movers (5)
	Panel A. Overdraft (unsecured credit lines)				
$\text{Overconfidence}_{\text{Math}}$	14.923***	15.493***	14.232***	14.176***	
	(3.049)	(3.706)	(2.833)	(2.808)	
HighRisk			0.740***		
			(0.018)		
$\text{Overconfidence}_{\text{Math}}$ (Orig)					4.028***
					(0.636)
	4441397	4441397	4441397	4441397	1001130
R^2	0.124	0.089	0.167	0.175	0.181
	Panel B. Credit lines backed by account receivables				
$\text{Overconfidence}_{\text{Math}}$	10.278***	11.290***	9.993***	9.877***	
	(2.662)	(2.749)	(2.390)	(2.354)	
HighRisk			0.738***		
			(0.017)		
$\text{Overconfidence}_{\text{Math}}$ (Orig)					3.768***
					(0.514)
Observations	3641608	3641608	3641608	3641608	828248
R^2	0.270	0.280	0.418	0.439	0.456
	Panel C. Term loans				
$\text{Overconfidence}_{\text{Math}}$	4.984***	5.647***	4.658***	4.528***	
	(1.215)	(1.430)	(1.126)	(1.108)	
HighRisk			0.371***		
			(0.006)		
$\text{Overconfidence}_{\text{Math}}$ (Orig)					1.300***
					(0.282)
Observations	3219255	3219255	3219255	3219255	741647
R^2	0.362	0.348	0.408	0.420	0.435
Province-Year FE	N	N	N	N	Y
Geographic Controls	Y	Y	Y	Y	Y
Bank-Year FE	Y	Y	Y	Y	Y
Area-Year FE	Y	Y	Y	Y	-
Industry-Year FE	N	Y	Y	Y	Y
Other Firm Controls	N	N	Y	Y	Y
$\mathbb{1}$(Credit Score)-Year FE	N	N	N	Y	Y

Table A.8: **Overconfidence and Loan Applications: Robustness**

The dependent variable is at the bank-firm-year level. In Panel A it is a dummy equal to one if a firm applies to any bank in a given year, 0 otherwise; in Panel B it is equal to the log of credit if the application is accepted, 0 otherwise. $\text{Overconfidence}_{\text{Math}}$ is the province-level share of pupils who say that they find Mathematics easier than their classmates (INVALSI test). Geographic controls include: log GDP per capita, the length of bankruptcy proceedings, the region-averages from the preference survey in Falk et al. (2018). HighRisk is a dummy equal to one if the Cerved Altman Z-score index, ranging from 1 (lowest risk) to 9 (highest risk), is above 7. Area-year fixed-effects are North×Year and South×Year fixed-effects (where the omitted category is Center). Other firm controls include: current realized and past growth rate of sales, sales growth volatility in the past three years, EBITDA/assets, the (log of) firm age and total assets. 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)
	Panel A. 𝟙(Loan Application Made)			
$\text{Overconfidence}_{\text{Math}}$	0.140	0.102	0.208	0.210
	(0.338)	(0.311)	(0.270)	(0.272)
HighRisk			0.078***	
			(0.004)	
Observations	6450953	6450953	6450953	6450953
R^2	0.067	0.089	0.165	0.174
	Panel B. =Ln(Credit) if Accepted, 0 Otherwise			
$\text{Overconfidence}_{\text{Math}}$	-2.545*	-2.563*	-2.948**	-3.236**
	(1.291)	(1.299)	(1.413)	(1.375)
HighRisk			-0.125***	
			(0.021)	
Geographic Controls	Y	Y	Y	Y
Bank-Year FE	Y	Y	Y	Y
Area-Year FE	Y	Y	Y	Y
Industry-Year FE	N	Y	Y	Y
Other Firm Controls	N	N	Y	Y
𝟙(Credit Score)-Year FE	N	N	N	Y
Observations	848131	848131	848131	848131
R^2	0.037	0.044	0.050	0.056

Table A.9: **Is it Bank Overconfidence?**

The dependent variable is the loan acceptance rate at the bank-firm-year level. In Panel A it is a dummy equal to one if the application is accepted and in Panel B it is equal to the log of credit if the application is accepted, 0 otherwise. We exclude all banks with total assets below €2.1 billion (definition of a small cooperative bank according to Bank of Italy) in column (1); below €21 billion (small-medium bank) in column (2) and those below €100 billion (only top5 large bank) in column (3). $\text{Overconfidence}_{\text{Math}}$ is the province-level share of pupils who say that they find Mathematics easier than their classmates (INVALSI test). Standard errors presented in parentheses are clustered at the province level. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)
	Bank Assets		
	>€2.1 bil	>€21 bil	>€100 bil
Panel A.	𝟙(Loan Application Accepted)		
$\text{Overconfidence}_{\text{Math}}$	-0.270**	-0.308***	-0.269*
	(0.114)	(0.117)	(0.137)
Observations	710273	655656	432450
R^2	0.041	0.039	0.037
Panel B.	Ln(Credit) if Accepted, 0 Otherwise		
$\text{Overconfidence}_{\text{Math}}$	-3.379**	-3.825***	-3.306*
	(1.390)	(1.438)	(1.713)
Geographic Controls	Y	Y	Y
Area-Year FE	Y	Y	Y
Bank-Year FE	Y	Y	Y
Industry-Year FE	Y	Y	Y
𝟙(Credit Score)-Year FE	Y	Y	Y
Observations	710273	655656	432450
R^2	0.044	0.042	0.041

Table A.10: **Overconfidence, Collateral and Credit Supply: Robustness to Other Lending Factors**

The dependent variable is a dummy equal to one if the application is accepted. Overconfidence$_{\text{Math}}$ is the province-level share of pupils who say that they find Mathematics easier than their classmates (INVALSI test). The variables from the bank organizational survey are the answers to the following question: "when a borrower comes to your bank for the first time, how important are:" Quantitative Methods ("exclusively quantitative and statistical methods"), Balance Sheet ("borrower balance sheet data"), Credit Register ("information on existing credit relationships from credit register or other credit bureaus"), Qualitative Info ("qualitative information, such as firm organization, characteristics of the project"), Personal Knowledge ("other evaluations based on personal knowledge"), Collateral ("availability of guarantees, either real or personal"). The answers are reported as a ranking from 1 to 6, we standardize them so that higher values mean higher importance of that factor. Log(Dist) is the geographical distance between the province of the bank headquarter and that of the firm headquarter. Standard errors presented in parentheses are two-way clustered at the bank and province level. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)
	$\mathbb{1}$(Loan Application Accepted)				
Overconfidence$_{\text{Math}}$ × Collateral$_b$	0.357***	0.313***	0.366***	0.420***	0.304**
	(0.097)	(0.091)	(0.093)	(0.085)	(0.116)
Overconfidence$_{\text{Math}}$ × QuantitativeMethods$_b$	-0.101				
	(0.070)				
Overconfidence$_{\text{Math}}$ × BalanceSheet$_b$		-0.163***			
		(0.043)			
Overconfidence$_{\text{Math}}$ × CreditRegister$_b$			-0.047		
			(0.042)		
Overconfidence$_{\text{Math}}$ × QualitativeInfo$_b$				0.163***	
				(0.040)	
Overconfidence$_{\text{Math}}$ × PersonalKnowledge$_b$					0.137
					(0.088)
Log(Dist)	-0.009***	-0.008***	-0.008***	-0.008***	-0.008***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Overconfidence$_{\text{Math}}$×Bank Characteristics	Y	Y	Y	Y	Y
Bank-Year FE	Y	Y	Y	Y	Y
Firm-Year FE	Y	Y	Y	Y	Y
Observations	848131	848131	848131	848131	848131
R^2	0.492	0.492	0.492	0.492	0.492

Table A.11: **Overconfidence, Collateral and Credit Supply: Asset Tangibility**

The dependent variable is at the bank-firm-year level. In Panel A it is a dummy equal to one if the application is accepted and in Panel B it is equal to the log of credit if the application is accepted, 0 otherwise. $\text{Overconfidence}_{\text{Math}}$ is the province-level share of pupils who say that they find Mathematics easier than their classmates (INVALSI test). $\text{Tang/TotalAsset}_{t-1}$ the ratio of tangible (property, plant and equipment) over total assets at the (2-digit) sector level in year $t-1$. Geographic controls include: log GDP per capita, the length of bankruptcy proceedings, the region-averages from the preference survey in Falk et al. (2018). Area-year fixed-effects are North×Year and South×Year fixed-effects (where the omitted category is Center). Firm controls include: current realized and past growth rate of sales, sales growth volatility in the past three years, lagged EBITDA/assets, the (log of) firm age and total assets; the Cerved Altman Z-score index, ranging from 1 (lowest risk) to 9 (highest risk). t-stat presented in parentheses with standard errors clustered at the province level. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)
Panel A:	$\mathbb{1}$(Loan Application Accepted)			
$\text{Overconfidence}_{\text{Math}}$	-0.314**	-0.386***	-0.398***	-0.429***
	(-2.04)	(-2.96)	(-3.01)	(-3.32)
$\text{Overconfidence}_{\text{Math}}\times$	0.853***	0.865***	0.763***	0.800***
Tang/TotalAssets	(3.06)	(2.99)	(2.74)	(2.87)
Observations	848131	848131	848131	848131
R^2	0.043	0.044	0.050	0.056
Panel B:	=Ln(Credit) if Accepted, 0 Otherwise			
$\text{Overconfidence}_{\text{Math}}$	-4.270**	-5.166***	-5.081***	-5.492***
	(-2.24)	(-3.15)	(-3.07)	(-3.39)
$\text{Overconfidence}_{\text{Math}}\times$	11.70***	11.86***	9.712***	10.27***
Tang/TotalAssets	(3.22)	(3.14)	(2.75)	(2.89)
Geographic Controls	N	Y	Y	Y
Area-Year FE	Y	Y	Y	Y
Firm Controls	N	N	Y	Y
Bank-Year FE	Y	Y	Y	Y
Industry-Year FE	Y	Y	Y	Y
$\mathbb{1}$(Credit Score)-Year FE	N	N	N	Y
Observations	848131	848131	848131	848131
R^2	0.0433	0.0436	0.0532	0.0590

Table A.12: **Overconfidence, Collateral and Credit Supply: Ln(Credit)**

The dependent variable is equal to the log of credit if the application is accepted, 0 otherwise. $\text{Overconfidence}_{\text{Math}}$ is the province-level share of pupils who say that they find Mathematics easier than their classmates (INVALSI test). Collateral is the answer to the bank delegation survey regarding the following question: "when a borrower comes to your bank for the first time, how important is: i) guarantees, either real or personal". The answers are reported as a ranking from 1 to 6, we standardize them so that higher values mean higher importance of that factor. Geographic controls include: log GDP per capita, the length of bankruptcy proceedings, the region-averages from the preference survey in Falk et al. (2018). Log(Dist) is the geographical distance between the province of the bank headquarter and that of the firm headquarter. Standard errors presented in parentheses are two-way clustered at the bank and province level. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)
	=Ln(Credit) if Loan Application Accepted, 0 Otherwise				
$\text{Overconfidence}_{\text{Math}} \times \text{Collateral}_b$	3.118***	4.483***	4.927***	4.913***	4.939***
	(1.151)	(1.260)	(1.335)	(1.328)	(1.303)
Collateral_b	-2.232**				
	(0.868)				
$\text{Credit Score} \times \text{Collateral}_b$				-0.008	
				(0.011)	
$\text{Overconfidence}_{\text{Math}} \times \text{Capital}$			0.562	0.558	0.615
			(0.569)	(0.565)	(0.574)
$\text{Overconfidence}_{\text{Math}} \times \text{NPL/Assets}$			0.528	0.526	0.530
			(0.380)	(0.380)	(0.379)
$\text{Overconfidence}_{\text{Math}} \times \text{Log(Assets)}$			0.627	0.627	0.619
			(0.621)	(0.621)	(0.621)
Log(Dist)	-0.144***	-0.107***	-0.106***	-0.106***	-0.106***
	(0.039)	(0.018)	(0.018)	(0.018)	(0.019)
Firm-Year FE	Y	Y	Y	Y	Y
Bank-Year FE	N	Y	Y	Y	Y
Collateral-$\mathbb{1}$(Credit Score)-Year FE	N	N	N	N	Y
Observations	848131	848131	848131	848131	848131
R^2	0.473	0.491	0.491	0.491	0.492

Table A.13: **Overconfidence, Collateral and Credit Supply: Robustness to Other Geographic Factors**

The dependent variable is a dummy equal to one if the application is accepted. $\text{Overconfidence}_{\text{Math}}$ is the province-level share of pupils who say that they find Mathematics easier than their classmates (INVALSI test). Log(Dist) is the geographical distance between the province of the bank headquarter and that of the firm headquarter. Standard errors presented in parentheses are two-way clustered at the bank and province level. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)
	$\mathbb{1}$(Loan Application Accepted)		
$\text{Overconfidence}_{\text{Math}} \times \text{Collateral}_b$	0.426***	0.441***	0.243***
	(0.104)	(0.094)	(0.091)
$\text{Collateral}_b \times$ Patience	0.019		
	(0.020)		
$\text{Collateral}_b \times$ Risk Taking	-0.019		
	(0.020)		
$\text{Collateral}_b \times$ Trust	-0.002		
	(0.020)		
$\text{Collateral}_b \times$ Altruism	0.005		
	(0.011)		
$\text{Collateral}_b \times$ Positive Reciprocity	0.005		
	(0.009)		
$\text{Collateral}_b \times$ Negative Reciprocity	-0.001		
	(0.010)		
$\text{Collateral}_b \times$ Log(GDP/Pop)		-0.000	
		(0.009)	
$\text{Collateral}_b \times$ LawInefficiency		-0.000	
		(0.004)	
$\text{Collateral}_b \times$ South			0.008
			(0.005)
Log(Dist)	-0.008***	-0.008***	-0.008***
	(0.001)	(0.001)	(0.001)
$\text{Overconfidence}_{\text{Math}} \times$Bank Characteristics	Y	Y	Y
Bank-Year FE	Y	Y	Y
Firm-Year FE	Y	Y	Y
Observations	848131	848131	848131
R^2	0.492	0.492	0.492