Corporate Overconfidence and Bank Lending

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August 11, 2022

Abstract

We study how banks lend to overconfident managers. For identification, we exploit variation in pupils' overconfidence across areas in Italy. We find that overconfident borrowers default more, pay higher loan rates and are more likely to be denied credit. Consistent with a model of bank lending where borrowers have biased beliefs, banks that ask for more collateral are less likely to restrict credit to overconfident borrowers. However overconfident borrowers, unlike those with high credit risk, are not disciplined by collateral requirements, as they invest and default more when they borrow from banks that rely more on collateral.

Keywords: overconfidence; loan applications; default; corporate investment; collateral requirements.
JEL: G41, G21

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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] While a number of empirical studies have explored the implications of managerial overconfidence on real and financial corporate outcomes, such as investment, mergers and debt maturity (Malmendier and Tate, 2005, 2008; Landier and Thesmar, 2008; Ben-David et al., 2013), there is no evidence on how banks lend to overconfident managers. This is a key question to understand the economic impact of overconfidence: if banks deny credit to overconfident managers who want to raise external funds and increase the scale of their operations. the economic impact of overconfidence might be limited.

Investigating the effects of managerial 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 at the borrower level.[2] 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 challenges and provide the first empirical evidence on the impact of managerial overconfidence on banks' credit supply decisions and ultimately on corporate investment and default.

We measure credit supply decisions using exhaustive data on firm-bank credit from the Italian Credit Register, including information on borrowers' credit scores, and their loan applications. To identify the effect of overconfidence on loan outcomes, we construct

[1]For example, Cooper et al. (1988) find that 68% of entrepreneurs perceive their odds of success as better than others and only 5% perceive their own chances as worse. In economics, 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]There are two common ways to measure managerial overconfidence: late option-exercise and popular press characterizations or positive forecast errors from firm-level surveys. The latter measure is the only one available for unlisted firms, such as those in our sample. Positive forecast errors might not necessarily reflect overconfidence, but rather the occurrence of unexpected negative shocks that induce rational errors ("bad luck").

variation across provinces in Italy using the share of local students in the national education attainment test (INVALSI) who claim that they find Mathematics easier than their classmates.[3] We consider overconfidence to be a local cultural trait and we hypothesize that pupils' overconfidence about their own ability in Math will also reflect the intrinsic overconfidence of local managers. This is 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). Using pupils' local overconfidence as a proxy for local borrowers' overconfidence 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 Manove and Padilla, 1999; Landier and Thesmar, 2008), and assume that overconfident managers (wrongly) interpret bad news on their projects as being good. We derive credit outcomes depending on the degree of firms' asset pledgeability, in a setting where competitive banks are able to observe whether borrowers are overconfident or not. The model delivers three key empirical predictions: overconfident borrowers on average (i) make positive forecast errors on their future revenues; (ii) are less likely to be denied credit by banks when their assets can be easily collateralized, in which case (iii) they are more likely to invest, and to default ex-post.

We first document a robust relationship between pupils' overconfidence and the likelihood of local firms to issue overly-optimistic forecasts on their future sales growth. Moreover, 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 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).[4]

[3]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.

[4]Our measure of overconfidence may be correlated with other characteristics of the local economy or with the quality of local institutions. For example, overconfidence is higher in areas with low GDP per capita and

We then investigate the effects of local borrowers' overconfidence on credit outcomes. We document that firms located in overconfident areas have a higher likelihood to default, pay higher interest rates on their loans, have a higher share of credit backed by collateral and their loan applications are less likely to be accepted. That is, we find that banks restrict credit to overconfident borrowers. 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 to evaluate its riskiness (Manove et al., 2001; Inderst and Mueller, 2006).[5]

Next, we ask whether collateral requirements reinforce or mitigate the disciplinary effects of banks on overconfident borrowers. In standard models of credit markets with rational borrowers, collateral requirements have been shown to mitigate both ex ante and ex post asymmetric information problems (e.g. Bester, 1985; Besanko and Thakor, 1987; Boot and Thakor, 1994; Thakor and Udell, 1991). However, when borrowers are overconfident, i.e. they are unaware of the risks they take, asking for collateral will not deter them from borrowing and from over-investing, resulting in higher ex-post default rates. We find that banks that attribute higher importance to collateral in their lending decisions to first-time borrowers are more likely to accept loan applications from overconfident borrowers, and grant them larger loans upon acceptance.[6]

Finally, we explore the real implications of our findings for corporate investment. Previous work has shown that overconfident managers invest more than rational managers.[7] We

low levels of trust or social capital (Guiso et al., 2004; Falk et al., 2018). However, the negative correlation is fully captured by macro-area dummies for the North and South of the country, which we always include in all our regressions (as time-varying dummies).

[5]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 repeat the analysis and find similar results (i) within the subsample of large banks, whose lending decisions tend to follow uniform rules (Liberti et al., 2016), and (ii) within the subsample of large firms whose loan applications, given the size of the requested amount, are more likely to require authorization from banks' headquarters.

[6]The results are not confounded by differences in borrowers' credit risk: we do not find that high-collateral banks lend more to firms with high credit risk, but only to overconfident borrowers. Moreover, results are unchanged when we include collateral$\times$credit score dummies$\times$year fixed-effects, to fully absorb unobserved heterogeneity of credit allocation by high-collateral banks.

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

confirm this result in our data. However, our novel contribution is to show that this result is amplified by the collateral lending channel: the sensitivity of investment (and ex-post default) to overconfidence is significantly higher for firms that borrow from banks that rely on collateral-based lending. Crucially, this does not hold for borrowers with high credit risk, who invest and default less when they borrow from collateral-based banks. This finding 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 and how collateral requirements may decrease credit market efficiency.

In the last part of the paper, we address the potential remaining concern that omitted local variables other than overconfidence (and the list of geographical and cultural factors already included as controls in our specifications) could be driving our results. For this, we focus on movers, i.e. managers of firms located in a different province from the one they were born in. This allows us to include fixed effects for the province the firm is located in, thus controlling for observed and unobserved characteristics of the area where the firm is located, such as the degree of local economic development, or the quality of institutions. As moving is not random, we check that movers end up in firms with ex-ante observable characteristics similar to those that employ non-movers. Reassuringly, all our results hold when we restrict our sample to movers.

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).[8] There is also a fast-growing literature studying the implications of lenders' biased beliefs for the economy, especially in

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

the context of boom and bust episodes (see e.g. Greenwood and Hanson, 2013; Bordalo et al., 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 managerial overconfidence on the economy.

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). 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 executives receive less total compensation than their peers and Adam et al. (2020) document that they are more likely to select syndicated loan contracts that are performance-sensitive. 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 direct evidence on how borrowers' overconfidence affects banks' credit supply.

Finally, our results provide novel insights to the literature studying the benefits and costs of collateral in debt contracts. The theoretical literature typically motivates collateral as a screening device to attenuate adverse selection ex-ante (Bester, 1985; Besanko and Thakor, 1987), and as a way of reducing various 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, higher interest rates, and higher ex-post default (Berger and Udell, 1990; Kose et al., 2003; Jimenez 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 and default less when required to pledge collateral, our contribution is to provide the first empirical evidence on the distortionary effects of collateral through borrowers' overconfidence.

The remainder of the paper is organized as follows. In Section 2 we derive testable predictions for the role of collateral in lending to overconfident borrowers. We present our data in Section 3 and our empirical strategy in Section 4. Section 5 presents the baseline results on credit outcomes, whereas Section 6 focuses on the effect of banks' collateral requirements. Section 7 explores the implications of overconfidence and collateral-based lending for corporate investment. Section 8 presents specifications restricted to movers. Section 9 concludes.

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),[9] 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 et al., 2022) Instead, collateral does not allow to screen for overconfident borrowers, but lead them to invest and default more, as by definition they are not conscious of their own biases.

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 less likely to be denied credit by banks when their assets can be easily collateralized, 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. always adopting Growth 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 en-

[9]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.

trepreneur 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 with probability one if the project is Good and the Safe strategy with probability one if the project is Bad. Overconfident entrepreneurs 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.[10] 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 on the firm's asset in place $A < I$, which are seized in case of default. The value of collateral for the bank is $\chi A < A$.

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

[10] In doing so, we borrow the notion of informed lending from Inderst and Mueller (2006). 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 $\alpha\,(I - \chi A) > 0$.

the growth strategy).[11] 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:

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

An overconfident borrower always perceives signals as being good, and therefore believes (wrongly when the project is in fact bad) that the realized return at $t = 2$ will be R_{Gr}. Note that the cost of external finance is decreasing in χ. When firms' assets cannot be pledged ($\chi = 0$), Π^{Opt} is negative and overconfident borrowers are credit-constrained (for their own good). Instead, when χ is large enough, i.e. when the firms' assets are easy to collateralize, 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

We use different sources of information, and report summary statistics in Table 1 for the different components of our final dataset. 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 school evaluation stan-

[11] 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.

dardized test on Italian and Mathematics that has been introduced in 2009 to evaluate school productivity and is compulsory for all primary school students in Italy. We obtain the individual students' answers for three waves (2009-2010, 2011-2012, 2012-2013).[12]

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 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.[13] 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), this is 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".[14]

[12]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.

[13]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.

[14]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

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, revolving lines of credit), credit lines backed by trade receivables and term loans.[15] 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 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.[16] 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).

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.

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

[16] 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).

3.3 INVIND survey on firm expectations

The Survey on industrial and service firms, hereafter 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. The survey questionnaire, 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. Survey respondents are typically the Chief Financial Officer (CFO) or other senior financial officers for larger firms and the Chief Executive Officer (CEO) for smaller firms, and the individual answers to the survey are confidential and are released to the public for statistical purposes in aggregate form only.[17] Having access to confidential answers attenuates the concern about 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 therefore not available to banks.

We also link the 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, which are the survey respondents in INVIND. From the tax identifier we are then able to identify the place of birth of the manager, which we use in subsequent analyses.

Measuring corporate 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:

[17] 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.

$FE_{t+1|t} = F_t(SalesGr_{t+1}) - SalesGr_{t+1}$, 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 make positive forecast errors, predicting sales growth to be 1.7 percentage points higher than they actually are and a significant fraction of firms (24%) make large, positive forecast errors in excess of 10 percentage points. As shown in Figure A.2 in the Online Appendix, firms with managers that make positive forecast errors in the INVIND survey are also unconditionally more likely to default than other firms.[18] 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 fixed-effects (see Table A.1 in the Online Appendix).[19]

3.4 Survey on inflation and growth expectations

The Survey on Inflation and Growth Expectations, hereafter 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.

[18]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 $FE_{t+1|t} < 0$.

[19]These include: firms' contemporaneous realized sales growth between year t and $t+1$ ($SalesGr_{i,t+1}$), lagged sales growth, the 3-year volatility of sales (as a measure of uncertainty of the forecast target), firm age, assets, profitability, a dummy for high credit risk (if the Cerved Altman-Z score is above 7) industry×year, and credit score dummies interacted with year fixed-effects.

3.5 Survey on banks' lending practices

Our empirical analysis also exploits 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.[20] Banks were asked to report a number of information about their internal organizations, including their lending practices for first-time borrowers (question B3 in the survey, reproduced in the Online Appendix Figure A.3). Specifically, banks are asked to rank the relative importance of six factors related to quantitative or qualitative information or collateral (i.e. personal or real guarantees) when they grant credit to a new borrower. In the rest of the analysis, we exploit the heterogeneity across banks in the relative importance of collateral requirements in their lending decisions. Figure 1 presents the associated distribution across all banks participating to the survey in 2006.

4 Identification strategy

In order to credibly isolate the impact of borrowers' overconfidence, we construct a plausibly exogenous measure of local overconfidence using differences 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 level of beliefs in self-efficacy today (i.e. the beliefs in one's own ability to complete tasks) as measured by pupils' answers to the INVALSI survey.

[20] 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.2 in the Online Appendix).

[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.

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 different waves of the INVALSI survey.[22]

Formally, to isolate the impact of corporate overconfidence on their credit outcomes, we estimate the following equation at the firm-year (or firm-bank year) level:

$$Y_{i,j,p,t+1} = \beta \text{Overconfidence}_{\text{Math},p} + \lambda' X_p + \gamma' X_{i,t} + \mu_{j,t} + \epsilon_{i,t} \tag{1}$$

where $Y_{i,j,p,t}$ is a credit outcome, e.g. $Default_{i,j,p,t}$ the 1-year default rate probability of firm i in industry j at time t, and $\text{Overconfidence}_{\text{Math},p}$ is the share of pupils declaring to be better than their classmates in Mathematics in province p where the firm operates. $\mu_{j,t}$ is a 2-digit industry×year fixed-effect. In all regressions, standard errors are clustered at the province level to account for serial correlation of the error term within provinces. Because our goal is to isolate the effect of overconfidence from other local geographic and economic factors that are also likely to correlate with both pupils' overconfidence and credit outcomes, we control for a host of local geographic factors (X_p). For example, students in the South are more overconfident in their ability in Math than their fellow students in the North. At the same time, households in the South are characterized by low levels of social capital and trust in institutions (Guiso et al., 2004). All these factors are likely to affect credit outcomes and could potentially correlate with local overconfidence in students' own abilities.

In particular, we control for local social preferences using the Global Value Survey on people's attitudes toward risk, trust and social factors from Falk et al. (2018) which are available for 19 regions in Italy. Table A.4 in the Online Appendix shows that pupils' overconfidence

[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 on credit and collateral requirements presented below also hold if we use these alternative measures of pupils' overconfidence.

does not correlate with any of these local preferences, other than a weakly significant negative correlation with trust, which is actually fully captured by a South dummy (which we include in all our specifications). At the more granular province level (110 provinces) we can control for local economic development using the (log of) GDP per capita, for the inefficiency of law enforcement using the average number of days it takes to complete bankruptcy proceedings in the local courts, for education using the share of population with college degrees and for social capital using the measure from Guiso et al. (2004), i.e. voter turnout at referenda in Italy between 1946 and 1989 (available for 92 provinces). As shown in Table A.5 in the Online Appendix, pupils' overconfidence does not correlate with the degree of local economic development, or the quality of institutions, once we control for macro-area dummies for the North and South. 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 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 certainly not orthogonal to local socio-economic characteristics, the residual variation after controlling for these factors (in particular the macro-area dummies) is plausibly exogenous.

In the last part of the paper, we address the potential remaining concern that omitted local variables other than overconfidence (and the list of geographical and cultural factors already included as controls in our specifications) could confound our estimates. For this, we focus on movers, i.e. managers of firms located in a different province from the one they were born in. This allows us to include fixed effects for the province the firm is located in, thus controlling for observed and unobserved characteristics of the area where the firm is located, such as the degree of local economic development, or the quality of institutions. As moving is not random, we check that movers end up in firms with ex-ante observable characteristics similar to those that employ non-movers. Reassuringly, all our main results hold when we restrict our sample to movers.

5 Results

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 of local firms to issue overly-optimistic forecasts ($\mathbb{1}(FE > 0.1)$) about their future sales in the INVIND sample. Figure 3 suggests pupils' overconfidence in Mathematics or Italian has a strong positive correlation with large 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 Table 2. We start by including only 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) and year fixed-effects, we confirm the evidence in Figure 3 and find a statistically significant relationship between pupils' overconfidence and firms' forecast errors on their future sales. The effect is economically large: a one standard deviation increase in self reported ability in Math (+0.025) is associated with an increase in the probability of making a large positive forecast error by 10% compared to the mean.

[INSERT TABLE 2 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 environmental 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, including the 2007-08 financial crisis, in different areas and sectors (Barone et al., 2018); and finally credit score-year fixed effects in column (5). Overall, these results confirm that there is a strong and robust relationship between local pupils' and borrowers' overconfidence across Italian provinces.

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 (Coibion et al., 2019). The results are presented in Table 3.

[INSERT TABLE 3 HERE]

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). Finally, we check that, within the subset of firm respondents present in both surveys, those with higher future sales' forecasts in INVIND also expect an improvement in their own business conditions in the SIGE (Panel C). Taken together, these results make us confident that our approach allows us to isolate overconfidence from other determinants of firms' beliefs.

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 the precision of firms' forecast, as measured by the difference between the upper and lower bound interval of sales forecast, which some firms report in the INVIND survey (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 firm forecast error, rather than the dummy for a large positive forecast error ($\mathbb{1}(FE > 0.1)$ - 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 are good in Math but score below the median.

5.2 Loan default

We now estimate the effect of local borrowers' overconfidence on credit outcomes.[23] We start by estimating Equation 1 in which the dependent variable Y_i is the 1-year default probability of firm i.

[INSERT TABLE 4 HERE]

Results on loan defaults are presented in Table 4. The estimates show that firms headquartered in overconfident areas are more likely to default on their existing loans. Quantitatively, a 1 standard deviation increase (+0.025) in the share of pupils who say they are good in Math leads to 0.4 percentage points higher default rate, i.e. 19% higher probability of default compared to the mean. 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).[24] Similarly, the main coefficient of interest remains stable when we include industry times year fixed effects in column (2), firm characteristics in columns (3) and credit score-year fixed-effects in column (4). Among relevant firm characteristics, we highlight that high-risk firms are more than twice as likely to default as other firms.

5.3 Loan rates

Having established that local overconfidence affects default, and that this matters over and above quantitative information from credit scores or past performance, we then ask whether banks price this risk component in their loan rates. The results are presented in Table 5.

[INSERT TABLE 5 HERE]

[23]In what follows, we use our instrument in reduced form, regressing the overconfidence of local pupils directly on credit outcomes, instead of using it in IV-2SLS because in this way we can make full use of the Italian CR data and we are not restricted by the firms present in the INVIND survey (the only ones for which we observe forecast errors). The evidence in Section 5.1 is thus akin to a first-stage regression, showing that local pupils' overconfidence affects local managerial overconfidence.

[24]The magnitude of the effects are also similar (9-13% higher default probability compared to the mean) if we look at 2-year or 3-year default probabilities (Table A.7 in the Online Appendix).

We find a positive and statistically significant association between local overconfidence and average loan rates. Importantly, the economic magnitude of the coefficient is large and indicates that the observed difference in interest rates is enough for banks to break-even on average when lending to overconfident borrowers: given that the average recovery rate in Italy in 2017 is 30% and the coefficient of overconfidence on default is 0.19 (see column (4) of Table 4), a simple back of the envelope calculation suggests that the coefficient on the loan rate for banks to break-even should be around $0.19 \times 0.7 = 13.3\%$. This is remarkably close to the estimated coefficients from Table 5, which are around 13.5%.[25]

Still, even though banks break-even on average when lending to overconfident borrowers, this does not mean that credit is *not* misallocated. Indeed in the simple model presented in Section 2, we show that credit is still misallocated when loans are collateralized, because in this case overconfident borrowers are not denied credit and end up investing in negative NPV projects.

5.4 Loan applications

We now turn to the implications of borrowers' overconfidence for the allocation of bank credit. In particular, we ask: are banks more likely to deny credit to overconfident borrowers?

[INSERT TABLE 6 HERE]

For 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] Table 6 reports the results. We first show that overconfident borrowers are not more likely to apply for credit than other firms. In fact, the effect of overconfidence on credit demand is theoretically ambiguous: on the one hand, overconfident borrowers may be inclined to ask for credit because they believe

[25] The results are similar if we distinguish average loan rates by different loan types (overdrafts, credit lines backed by receivables and term loans). See Table A.8 in the Online Appendix.

[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.

their project is good; on the other hand, they may be discouraged from applying because they think that external finance is too costly (Malmendier et al., 2011).

We then look at acceptance rates and amount of credit granted (Panel B and C of Table 6). The point estimates for overconfident borrowers are negative and statistically significant at the one percent level. Quantitatively, a one standard deviation increase in local overconfidence decreases the acceptance rate by about 0.63 percentage points, i.e. 2.5% lower compared to the mean acceptance rate. The results are consistent with a disciplinary role of banks when they face overconfident borrowers: since these have higher default rates (Table 4), they are credit constrained when they apply for a loan and when they obtain credit, they are charged more than others (Table 5). The effects are quantitatively similar to those for firms with high credit risk, which have acceptance rates that are 0.8 percentage points lower than others. In the next section, we will explore how collateral requirements imply differences in the reaction of overconfident and high-risk borrowers.

Are our results driven by bank overconfidence? If local entrepreneurs are overconfident, what about local loan officers? We run a series of empirical tests to 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.

Finally, we repeat the analysis (i) 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), and (ii) within the subsample of large firms, for which loan applications, given the size of the requested amount, are more likely to require authorization from banks' headquarters.

We present the results in Table A.9 in the Online Appendix. 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.

Moreover, the potential confounding impact of bank overconfidence is also addressed by the tests that we run in Section 8 on the sample of managers who moved, where we include fixed effects for the location 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 The Collateral Channel

In this section, we provide empirical tests for the model prediction that collateral requirements relax financial constraints for overconfident borrowers and lead them to over-borrow.

First of all, we show in Table 7 that overconfident borrowers, when they obtain credit, have a higher share of their loans backed by collateral compared to other borrowers. The results are economically significant: a one standard deviation increase in overconfidence leads to 5% higher share of collateralized loans compared to the mean. These effects are stable as we saturate the regression with fixed-effects and controls.

Next, we directly test whether banks that attribute higher importance to collateral in their lending decisions are more likely to accept loan applications from overconfident borrowers. For this, we exploit a unique bank survey run by Bank of Italy in 2006, where banks were asked to report details on their lending practices, and from which we can build a proxy for banks' self-reported reliance on collateral requirements when lending to new borrowers. Formally, we estimate the following equation:

$$Accept_{i,b,t} = \beta_1 \text{Overconfidence}_{\text{Math},p} + \beta_2 \text{Overconfidence}_{\text{Math},p} \times Collateral_b + \lambda Log(Dist_{i,b}) + \mu_{i,t} + \mu_{b,t} + \epsilon_{i,b,t} \quad (2)$$

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). 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.2 in the Online Appendix). Thus, collateral-based banks as per the survey definition actually lend more on a collateralized basis. 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. 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.

[INSERT TABLE 8 HERE]

We present the results in Table 8. 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 less likely to deny credit to overconfident firms. Importantly, since 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 for a bank that thinks that collateral is the least important factor ($\text{Collateral}_b = 1$) in lending to first-time borrowers leads to a decline in acceptance rate by 8% to virtually no effect for banks that value collateral the most ($\text{Collateral}_b = 6$). We then progressively saturate the regression with bank-year fixed-effects in column (2), thus absorbing bank-time unobserved heterogeneity (such as lending policies or bank overconfidence): the coefficient of the interaction term between overconfidence and the measure of banks' reliance on collateral remains remarkably stable.

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 (3) of Table 8, 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.[27]

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.[28] For this, in column (4) of Table 8 we include the interaction of Collateral_b and the dummy for high credit risk. We find that the coefficient is not significant, i.e. high collateral 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 (5), 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.

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 2 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 (which are easier to pledge as collateral). While the coefficient on the pupils' overconfidence is negative and significant, the interaction term with the asset tangibility ratio is positive and larger

[27] 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.

[28] 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)

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 8 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 high-collateral 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 amd 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

Our findings so far have shown that overconfident borrowers are more likely to default, and that bank heterogeneity in the reliance on collateral requirements matters for the allocation of credit to overconfident borrowers. A natural question is thus whether credit supply decisions made by collateral-based banks 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. This is in contrast to standard models with asymmetric information where borrowers with high credit risk, which are aware of their low-quality, are disciplined by collateral requirements. In this section, we aim to shed light on these questions.

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 that have a larger share of their total credit from collateral-based banks have a higher investment intensity. Results are presented in Table 9.

[INSERT TABLE 9 HERE]

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 is related to previous studies that find that miscalibrated managers invest more than other (Ben-David et al., 2013) and that overconfident managers over-invest internal resources (Malmendier and Tate, 2005).[29] The estimate implies that moving from the province with the lowest to the highest level of pupils' overconfidence is associated with a 2.2 percentage points (0.21×0.11) higher investment rate. This is a large economic effect, which represents a 20% increase compared to the average investment rate in our sample of firms.

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, by extending credit to overconfident borrowers, are fueling the investment made by overconfident managers. We construct the importance of collateral-based lending at the firm level by taking a a firm-year average of the answer to the question of

[29] 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.

collateral importance at bank level, where the weights are equal to the share of total credit from each bank to the firm. We find in column (2) that the higher sensitivity of investment to overconfidence is entirely driven by these banks: overconfident managers that borrow more from banks which value collateral have higher investment rates. This is a novel result in the literature and indicates that the effect of managerial overconfidence is amplified by the collateral lending channel: the sensitivity of investment to managerial overconfidence is higher for firms that borrow from banks that rely on collateral-based lending.

The higher investment sensitivity of overconfident borrowers is not due to credit risk: in column (3) of Table 9 we include the interaction of $\text{Collateral}_{f,t}$ and the dummy for high risk borrowers. The coefficient on the interaction of interest, $\text{Collateral}_{f,t} \times \text{Overconfidence}_{\text{Math},p}$, remains unchanged. Moreover, we find that high risk firms that borrow from high-collateral banks invest less than others. The negative coefficient shows that high-risk borrowers are disciplined by collateral requirements, consistent with standard theoretical predictions (Boot and Thakor, 1994; Thakor and Udell, 1991). Moreover, we include an exhaustive set of $\text{Collateral}_b\times$ credit score dummies $\times$ year fixed-effects in column (4), and again our coefficient of interest is unchanged. Finally, we show in column (5) that the higher investment rate of overconfident borrowers actually leads to higher ex-post default rates. This is again in stark contrast to borrowers with high-credit risk, who have lower default rates when they borrow from these banks.

Finally, we ask whether our estimates are quantitatively large enough to explain the distribution of non-performing loans in the cross-section of banks. In order to do this, we aggregate the amount of defaulted credit 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 NPLs. The results are presented in Online Appendix Table A.14. We confirm that default rates are sensitive to local pupils' overconfidence in specifications aggregated at the province-level. The coefficients are very similar to the ones we found for firm-level default rates in Table 4. We thus confirm 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.

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 lending efficiency when borrowers have biased beliefs.

8 Movers

Admittedly, controlling for a host geographic and cultural factors may not fully address the concern that some local characteristics other than overconfidence might be driving our results. To rule this out, one would need to control for a province fixed-effect, which however would also absorb the effect of local overconfidence on firm forecast errors and loan outcomes. To circumvent this issue, 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. Movers are likely to be affected not only by the overconfidence of the place where they currently live, but also by the overconfidence of the place where they grew up. This effect is present if there is an inherited component in overconfidence, or if people's expectations are affected by their past experiences, which are determined by what people live through and observe around them, which in turn depends on location (Malmendier and Nagel, 2011). Regardless of the reason, this test allows us to include a province fixed-effect in our analysis, separating the effect of top managers' overconfidence from other local confounding factors, as in Guiso et al. (2004, 2021).

To run these tests, we restrict the sample to firms whose managers are defined as "movers". More specifically, we obtain managers' province of birth from their social security number available at the Italian Chamber of Commerce dataset ($Infocamere$). This sample is available from 2005. We then restrict the sample to firms whose top managers were born in a different province from where the firm headquarter is.[30] Most firms with movers (75%) are located

[30]The overall sample size in these specifications is smaller, because 70% of managers work in the same province where they were born. 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

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 risky firms. However, we do not find that the overconfident movers join ex-ante riskier firms: 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 (Table A.15 in the Online Appendix).

We then re-estimate all our main empirical specifications using pupils' self-reported ability in Math from the provinces where firms' managers are born, holding constant the province in which firms are located. We present the results in Table 10.

[INSERT TABLE 10 HERE]

In column (1), we find that the coefficient on the overconfidence of the province where the managers were born is positively and significantly correlated with the probability of making larger forecast errors, even after controlling for fixed-effects for the province where the firm is located. Moreover, we control for a wide array of other characteristics of the manager, including socio-economic and risk preference variables from the province of origin of the manager and demographic characteristics such as age and gender. Importantly, we also include a dummy for whether the manager was born in a province in the South, so that the coefficient on managerial overconfidence captures variation across provinces over and above the South-North divide in overconfidence.

Consistent with the baseline results on credit outcomes we also find that the degree of local overconfidence in the province in which the manager was born affects firms' default probabilities, interest rates, share of collateralized credit, acceptance rate by banks that value collateral more and corporate investment. Reassuringly, in all these specifications, the coefficients on our proxy for overconfidence in managers' birth area are very similar to the one in our baseline regressions, indicating that our results are not biased by other characteristics of

province of birth (which happens for 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).

the local economy in which firms' operates, but instead reflect the causal impact of managerial overconfidence on firms' lending outcomes.

9 Conclusion

In this paper, we ask how banks respond to borrowers who are overconfident in the quality of their projects. Since overconfidence is endogenous, our identification strategy relies on variation in overconfidence across local areas in Italy using pupils' self-reported ability in Mathematics relative to their classmates from the national education attainment test. 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.

We then document that overconfident borrowers are more likely to default on their existing loans, pay higher loan rates and have more loans backed by collateral. Banks are more likely to deny credit to overconfident borrowers, but only for loans that cannot be easily collateralized. These results are not driven by omitted local factors, because firms' outcomes of managers who moved are still affected by the overconfidence of the province in which they were born, controlling for observed and unobserved characteristics of the local area the firm is located in. Finally, overconfident borrowers invest more than others, and the sensitivity of investment to overconfidence is higher for firms that borrow from banks that value collateral the most. Overall, our findings shed light on the instrumental role of banks' credit supply decisions in shaping how managers' overconfidence affect economic outcomes.

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

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

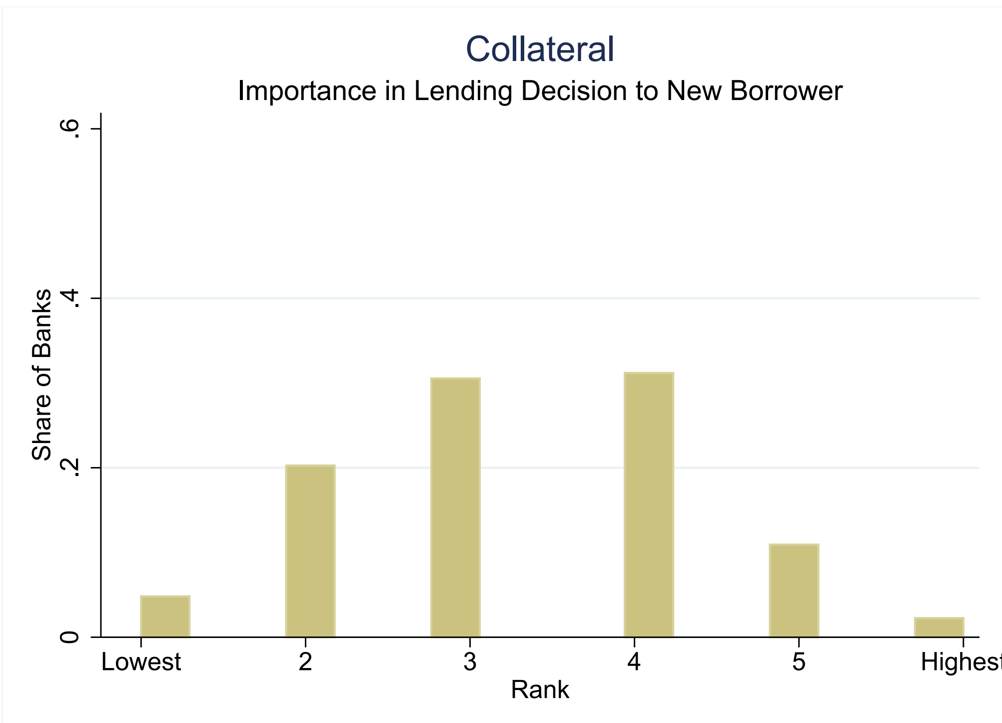


Figure 2: **Overconfidence in Mathematics**

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.

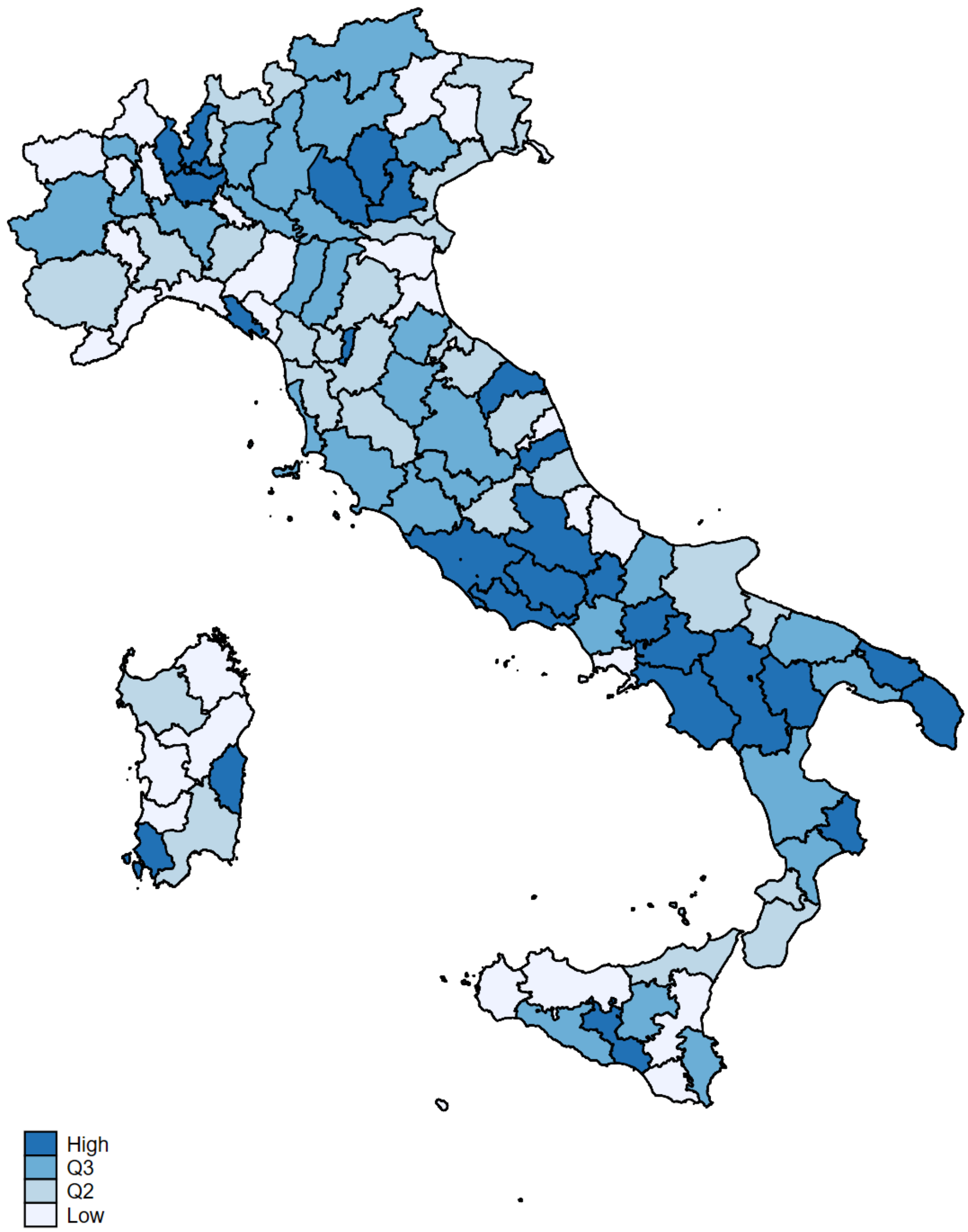
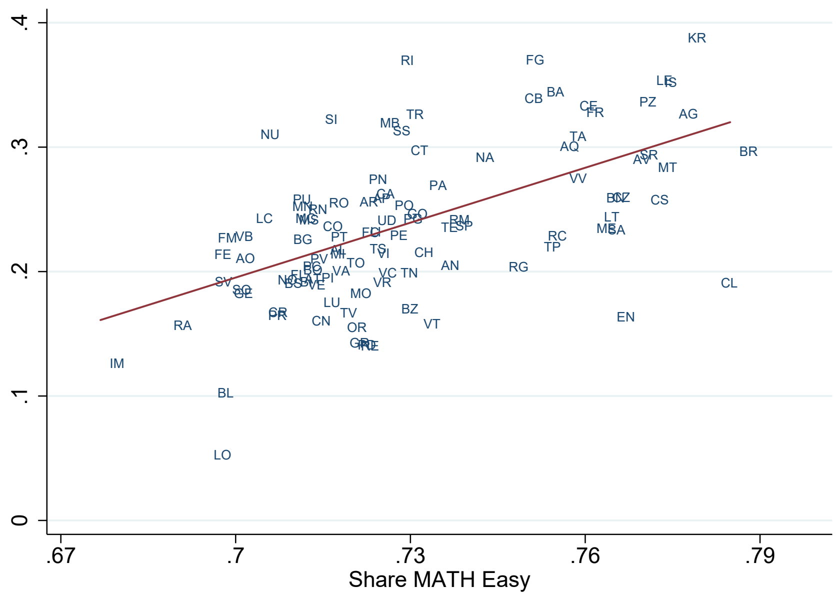


Figure 3: **Probability of Issuing Overconfident Forecast**

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$_{\text{Italian}}$

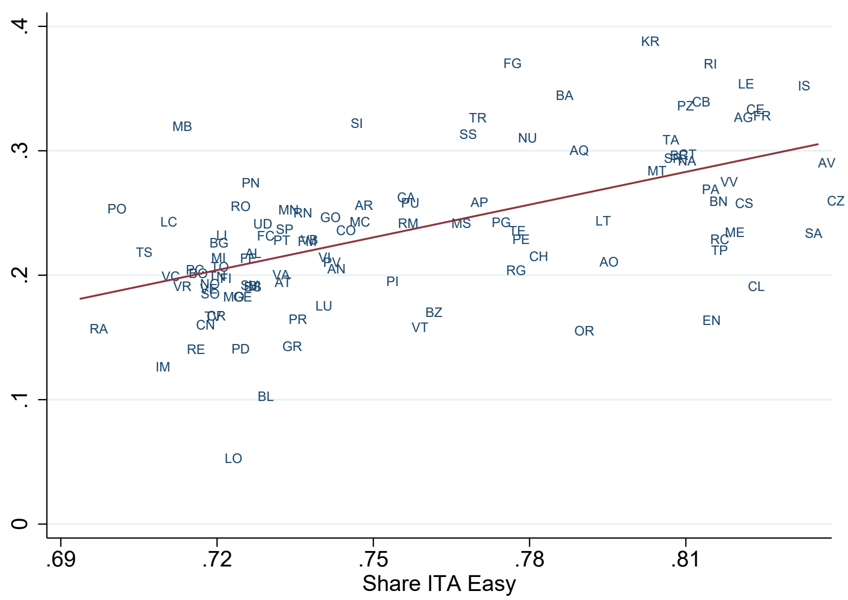


Table 1: **Summary Statistics**

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 (GDP per capita, 2001-2017 average; Law Inefficiency, the length of local bankruptcy proceedings) and regional level risk, time and social preferences from Falk et al. (2018) survey (Panel B); the full CR sample in 2001-2017 at both the firm (Panel C) and firm-bank 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 , firm-year level						
$FE_{i,t+1\|t} = (F_t(Sales_{i,t+1}) - Sales_{i,t+1})/Sales_{i,t}$	39656	0.017	0.181	-0.615	0.012	0.643
$\mathbb{1}(FE_{i,t+1\|t} < -0.1)$	39656	0.174	0.379	0.000	0.000	1.000
$\mathbb{1}(FE_{i,t+1\|t} > 0.1)$	39656	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)	39656	0.022	0.223	-0.581	0.016	0.759
Sales Growth Volatility	39656	0.155	0.170	0.008	0.103	0.957
Firm age (years)	39656	29.489	17.724	4.000	26.000	92.000
Firm Assets (€million)	39656	100.68	497.503	1.239	18.066	1554.8
EBITDA/Assets	39656	0.080	0.086	-0.174	0.074	0.356
Credit Score	39656	4.316	1.840	1.000	4.000	8.000
$\mathbb{1}$(Bad Debt in t+1)	39656	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, average per capita in €(2001-2017)	110	21478	5724	12679	21521	34776
Law Inefficiency	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-year level						
$\mathbb{1}$(Bad Debt in t+1)	3530830	0.025	0.155	0.000	0.000	1.000
$\mathbb{1}$(Bad Debt in t+2)	3530830	0.038	0.192	0.000	0.000	1.000
$\mathbb{1}$(Bad Debt in t+3)	3530830	0.056	0.229	0.000	0.000	1.000
Investment Rate ($\Delta FixAssets_t/FixAssets_{t-1}$)	3075965	0.111	0.452	-0.401	-0.017	1.54
Loan Rate in %	2136986	6.684	3.183	1.049	8.312	16.649
Collateralized Credit/Total	2720693	0.237	0.368	0.000	0.245	1.000
HighRisk	3530830	0.208	0.383	0.000	0.000	1.000
Firm Age (years)	3530830	17.269	12.730	3.000	14.000	60.000
Log(Firm Assets$_{t-1}$)	3530830	7.346	1.326	4.762	7.197	11.281
Sales Growth (t,t+1)	3530830	0.080	0.471	-0.790	0.018	3.024
Sales Growth Volatility	3530830	0.379	0.700	0.011	0.172	4.423
Panel D. New borrower applications, firm-bank-year level						
$\mathbb{1}$(Loan Application Made)	6450953	0.494	0.500	0.000	0.000	1.000
$\mathbb{N}$(Loan Applications Made)	6450953	0.615	0.750	0.000	0.000	3.000
$\mathbb{1}$(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
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: **Pupils' Overconfidence and Firm Forecast Errors**

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 from INVIND survey exceeds 10 percentage points, 0 otherwise. $\text{Overconfidence}_{\text{Math}}$ is the province-level share of pupils who say that they find Mathematics easier than their classmates (INVALSI). Geographic controls include: Patience, Risk Taking, Positive Reciprocity, Negative Reciprocity, Altruism, and Trust (region-averages from the preference risk survey in Falk et al. (2018)); the log of province-level GDP per capita in each year; the log of the province-average length of bankruptcy proceedings in days. 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)
	$\mathbb{1}(FE_{i,t+1\|t} > 0.1)$				
$\text{Overconfidence}_{\text{Math}}$	1.014***	0.864***	0.815***	0.606***	0.606***
	(0.147)	(0.217)	(0.227)	(0.215)	(0.212)
Firm Controls	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
$\mathbb{1}$(Credit Score)-Year FE	N	N	N	N	Y
Observations	42437	42437	42437	42437	42437
R^2	0.246	0.247	0.247	0.281	0.284

Table 3: **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 4: **Overconfidence and Default**

The dependent variable is the 1-year probability of default (=1 if firm loan becomes bad debt in year t+1) at the firm-year level. $\text{Overconfidence}_{\text{Math}}$ 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)
	$\mathbb{1}$(Bad Debt in t+1)			
$\text{Overconfidence}_{\text{Math}}$	0.185***	0.182***	0.193***	0.192***
	(0.042)	(0.042)	(0.040)	(0.040)
HighRisk			0.035***	
			(0.001)	
Geographic Controls	Y	Y	Y	Y
Other Firm Controls	N	N	Y	Y
Area-Year FE	Y	Y	Y	Y
Industry-Year FE	N	Y	Y	Y
$\mathbb{1}$(Credit Score)-Year FE	N	N	N	Y
Observations	3530830	3530830	3530830	3530830
R^2	0.004	0.006	0.022	0.037

Table 5: **Overconfidence and Loan Rates**

The dependent variable is the average interest rate at the firm-year level. $\text{Overconfidence}_{\text{Math}}$ 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)
	Average Loan Rate (%)			
$\text{Overconfidence}_{\text{Math}}$	13.627***	13.391***	13.512***	13.524***
	(2.880)	(2.814)	(2.802)	(2.806)
HighRisk			0.319***	
			(0.021)	
Geographic Controls	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
$\mathbb{1}$(Credit Score)-Year FE	N	N	N	Y
Observations	2136986	2136986	2136986	2136986
R^2	0.093	0.100	0.122	0.127

Table 6: **Overconfidence and Loan Applications**

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 a dummy equal to one if the application is accepted and in Panel C 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. $\mathbb{1}$(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. $\mathbb{1}$(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)	
Observations	848131	848131	848131	848131
R^2	0.037	0.044	0.050	0.056
	Panel C. =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
$\mathbb{1}$(Credit Score)-Year FE	N	N	N	Y
Observations	848131	848131	848131	848131
R^2	0.037	0.044	0.050	0.056

Table 7: **Overconfidence and Collateralized Credit**

The dependent variable is the share of credit backed by collateral at the firm-year level. 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)
	Collateralized Credit/Total			
Overconfidence$_{\text{Math}}$	0.521**	0.518**	0.529**	0.513**
	(0.253)	(0.248)	(0.248)	(0.248)
HighRisk			0.043***	
			(0.003)	
Geographic Controls	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
$\mathbb{1}$(Credit Score)-Year FE	N	N	N	Y
Observations	2720693	2720683	2720683	2720683
R^2	0.018	0.106	0.122	0.116

Table 8: **Overconfidence, Collateral and Credit Supply**

The dependent variable is a dummy equal to one if the loan 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_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). 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)
	$\mathbb{1}$(Loan Application Accepted)				
$\text{Overconfidence}_{\text{Math}} \times \text{Collateral}_b$	0.265***	0.368***	0.405***	0.403***	0.405***
	(0.094)	(0.102)	(0.108)	(0.107)	(0.105)
Collateral_b	-0.189***				
	(0.070)				
$\text{HighRisk} \times \text{Collateral}_b$				-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)	-0.012***	-0.008***	-0.008***	-0.008***	-0.008***
	(0.003)	(0.001)	(0.001)	(0.002)	(0.002)
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 9: **Overconfidence, Collateral and Investment (and ex-post Default)**

The dependent variable is the firm-level yearly investment rate, i.e. the change in fixed-assets over lagged fixed assets in columns (1)-(4) and the 1-year probability of default (=1 if a loan of the firm becomes bad debt in year t+1) in column (5). $\text{Overconfidence}_{\text{Math}}$ is the province-level share of pupils who say that they find Mathematics easier than their classmates (INVALSI test). $\text{Collateral}_{f,t}$ 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.

	(1)	(2)	(3)	(4)	(5)
	Investment Rate				Default
$\text{Overconfidence}_{\text{Math}}$	0.206***	0.007	0.001	0.007	0.158***
	(0.050)	(0.064)	(0.062)	(0.064)	(0.041)
$\text{Collateral}_{f,t}$		-0.109***	-0.106***		0.006***
		(0.010)	(0.011)		(0.001)
$\text{Overconfidence}_{\text{Math}} \times \text{Collateral}_{f,t}$		0.128***	0.132***	0.130***	0.008***
		(0.014)	(0.014)	(0.014)	(0.001)
$\text{HighRisk} \times \text{Collateral}_{f,t}$			-0.006***		-0.004***
			(0.001)		(0.001)
Geographic controls	Y	Y	Y	Y	Y
Area-Year FE	Y	Y	Y	Y	Y
Industry-Year FE	Y	Y	Y	Y	Y
$\mathbb{1}$(Credit Score)-Year FE	Y	Y	Y	-	Y
Firm Controls	Y	Y	Y	Y	Y
Collateral-$\mathbb{1}$(Credit Score)-Year FE	N	N	N	Y	N
Observations	3075965	3075965	3075965	3075965	3117343
R^2	0.034	0.035	0.0354	0.0350	0.040

Table 10: **Movers**

The sample is restricted to firms whose senior managers (CEO, CFO and other top executives) were born in a different province from where the firm headquarter is located. The dependent variable is the firm forecast error on sales growth in column (1); the 1-year probability of default in column (2); the share of credit backed by collateral in column (3); the interest rate on revolving credit lines in column (4); a dummy equal to one if the application is accepted in columns (5) and the firm-level yearly investment rate in column (6). $\text{Overconfidence}_{\text{Math}}$ (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. South (Orig) is a dummy equal to one if at least one of the senior manager comes from a province in the South; Log(Age Manager) is average age of senior managers and Female Manager is a dummy equal to one if at least one of the senior managers is female. 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. Other 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). Standard errors presented in parentheses are clustered at the province level. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	$\mathbb{1}(FE > 0.1)$	Default	Collateral	Loan Rate	$\mathbb{1}$(Accepted)	Investment
$\text{Overconfidence}_{\text{Math}}$ (Orig)	0.827**	0.098**	0.301***	2.949*		-0.128*
	(0.352)	(0.049)	(0.110)	(1.616)		(0.074)
$\text{Overconfidence}_{\text{Math}}$ (Orig) × Collateral					0.301***	0.104***
					(0.086)	(0.025)
South (Orig)	-0.020	0.005***	0.012**	0.174***		0.004**
	(0.014)	(0.002)	(0.006)	(0.064)		(0.02)
Log(Age Manager)	-0.027	-0.007***	0.041***	-0.160		-0.049***
	(0.021)	(0.002)	(0.008)	(0.108)		(0.003)
Female Manager	-0.007	0.001	0.037***	0.008		-0.005***
	(0.009)	(0.001)	(0.003)	(0.043)		(0.001)
Province FE	Y	Y	Y	Y	-	Y
Area-Year FE	Y	Y	Y	Y	-	Y
Other manager charact.	Y	Y	Y	Y	-	Y
Industry-Year FE	Y	Y	Y	Y	-	Y
$\mathbb{1}$(Credit Score)-Year FE	Y	Y	Y	Y	-	Y
Firm-Year FE	N	N	N	N	Y	N
Bank-Year FE	N	N	N	N	Y	N
Overconf.×Bank controls	N	N	N	N	Y	N
Observations	12682	635136	446612	448020	163080	590536
R^2	0.344	0.043	0.167	0.032	0.500	0.036

Online Appendix

Corporate Overconfidence and Bank Lending

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

A Appendix Figures and Tables

Figure A.1: **INVALSI Survey**

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	☐	☐

Note: 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.*

Figure A.2: **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.

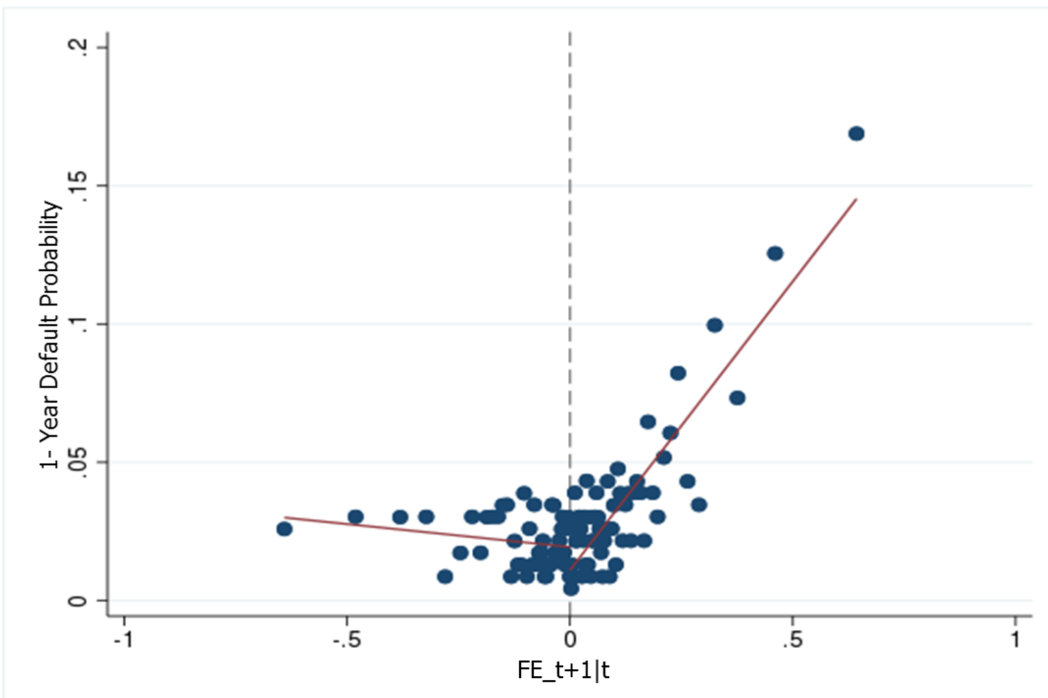


Figure A.3: **Bank of Italy Survey on the Lending Practices of Italian Banks**

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		

Note: 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.

Table A.1: **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.2: **Bank collateral survey and collateral usage: 2001-2017**

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.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: **Overconfidence and Social, Risk and Time Preferences**

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 *** denote significance at the 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Overconfidence$_{\text{Math}}$							
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

Table A.5: **Overconfidence and Other Province Characteristics**

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. 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); Log(GDP/Pop) is the log of average GDP per capita in 2001-2017; South (North) is a dummy equal to one for provinces located in the South (North) of Italy (the Center represents the omitted category); 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. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Overconfidence$_{\mathrm{Math}}$					
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					-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 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: Overconfidence ITA 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)				
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. $(F_t(Sales_{i,t+1}) - Sales_{i,t+1})/Sales_{i,t}$				
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. $\mathbb{1}(FE_{i,t+1}) > 0.1$				
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 Default: Robustness**

The dependent variable is the 2-year probability of default in Panel A and the 3-year probability of default in Panel B. $\text{Overconfidence}_{\text{Math}}$ 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). 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.

	(1)	(2)	(3)	(4)
	Panel A. $\mathbb{1}$(Bad Debt in t+2)			
$\text{Overconfidence}_{\text{Math}}$	0.201***	0.191***	0.196***	0.195***
	(0.049)	(0.049)	(0.045)	(0.044)
Observations	3530830	3530830	3530830	3530830
R^2	0.005	0.008	0.039	0.054
	Panel B. $\mathbb{1}$(Bad Debt in t+3)			
$\text{Overconfidence}_{\text{Math}}$	0.217***	0.200***	0.196***	0.193***
	(0.062)	(0.064)	(0.057)	(0.055)
Geographic Controls	Y	Y	Y	Y
Firm Controls	N	N	Y	Y
Area-Year FE	Y	Y	Y	Y
Industry-Year FE	N	Y	Y	Y
$\mathbb{1}$(Credit Score)-Year FE	N	N	N	Y
Observations	3530830	3530830	3530830	3530830
R^2	0.010	0.014	0.055	0.068

Table A.8: **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. $\text{Overconfidence}_{\text{Math}}$ 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. Overdraft			
$\text{Overconfidence}_{\text{Math}}$	16.460***	15.559***	15.454***	15.440***
	(4.222)	(4.034)	(4.041)	(4.046)
HighRisk			0.275***	
			(0.045)	
Observations	2136986	2136986	2136986	2136986
R^2	0.027	0.036	0.037	0.040
	Panel B. Credit Lines Backed by Receivables			
$\text{Overconfidence}_{\text{Math}}$	11.884***	11.607***	12.019***	11.913***
	(2.684)	(2.577)	(2.604)	(2.582)
HighRisk			0.693***	
			(0.018)	
Observations	1432870	1432869	1432869	1432869
R^2	0.226	0.266	0.382	0.400
	Panel C. Term Loans			
$\text{Overconfidence}_{\text{Math}}$	6.286***	6.075***	6.237***	6.166***
	(1.457)	(1.420)	(1.419)	(1.406)
HighRisk			0.321***	
			(0.006)	
Observations	1509291	1509290	1509290	1509290
R^2	0.343	0.353	0.390	0.400
Geographic Controls	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
$\mathbb{1}$(Credit Score)-Year FE	N	N	N	Y
Observations	2136986	2136986	2136986	2136986
R^2	0.093	0.100	0.122	0.127

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. In column (1) we exclude all banks with total assets below €100 billion; in column (2)-(3) we exclude all firm with sales below €1-10 million. 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 >100 bil	Firm Sales >1 mil	Firm Sales >10 mil
Panel A.	$\mathbb{1}$(Loan Application Accepted)		
Overconfidence$_{\text{Math}}$	-0.308***	-0.269*	-0.208
	(0.117)	(0.136)	(0.140)
Observations	432450	594482	193757
R^2	0.036	0.064	0.093
Panel B.	Ln(Credit) if Accepted, 0 Otherwise		
Overconfidence$_{\text{Math}}$	-3.825***	-3.306*	-2.714
	(1.374)	(1.669)	(1.699)
Geographic Controls	Y	Y	Y
Area-Year FE	Y	Y	Y
Bank-Year FE	Y	Y	Y
Industry-Year FE	Y	Y	Y
$\mathbb{1}$(Credit Score)-Year FE	Y	Y	Y
Observations	432450	594482	193757
R^2	0.040	0.062	0.091

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. $\text{Overconfidence}_{\text{Math}}$ 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)				
$\text{Overconfidence}_{\text{Math}}$ × Collateral	0.357***	0.313***	0.366***	0.420***	0.304**
	(0.097)	(0.091)	(0.093)	(0.085)	(0.116)
$\text{Overconfidence}_{\text{Math}}$ × QuantitativeMethods	-0.101				
	(0.070)				
$\text{Overconfidence}_{\text{Math}}$ × BalanceSheet		-0.163***			
		(0.043)			
$\text{Overconfidence}_{\text{Math}}$ × CreditRegister			-0.047		
			(0.042)		
$\text{Overconfidence}_{\text{Math}}$ × QualitativeInfo				0.163***	
				(0.040)	
$\text{Overconfidence}_{\text{Math}}$ × PersonalKnowledge					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)
$\text{Overconfidence}_{\text{Math}}$×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				
$\text{Overconfidence}_{\text{Math}} \times$Collateral	3.118***	4.483***	4.927***	4.913***	4.939***
	(1.151)	(1.260)	(1.335)	(1.328)	(1.303)
Collateral	-2.232**				
	(0.868)				
Credit Score$\times$Collateral				-0.008	
				(0.011)	
$\text{Overconfidence}_{\text{Math}} \times$Capital			0.562	0.558	0.615
			(0.569)	(0.565)	(0.574)
$\text{Overconfidence}_{\text{Math}} \times$NPL/Assets			0.528	0.526	0.530
			(0.380)	(0.380)	(0.379)
$\text{Overconfidence}_{\text{Math}} \times$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)		
$\text{Overconfidence}_{\text{Math}}$ × Collateral	0.426***	0.441***	0.243***
	(0.104)	(0.094)	(0.091)
Collateral × Patience	0.019		
	(0.020)		
Collateral × Risk Taking	-0.019		
	(0.020)		
Collateral × Trust	-0.002		
	(0.020)		
Collateral × Altruism	0.005		
	(0.011)		
Collateral × Positive Reciprocity	0.005		
	(0.009)		
Collateral × Negative Reciprocity	-0.001		
	(0.010)		
Collateral × Log(GDP/Pop)		-0.000	
		(0.009)	
Collateral × LawInefficiency		-0.000	
		(0.004)	
Collateral × South			0.008
			(0.005)
Log(Dist)	-0.008***	-0.008***	-0.008***
	(0.001)	(0.001)	(0.001)
$\text{Overconfidence}_{\text{Math}}$×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

Table A.14: **Overconfidence and Aggregate Default: Provinces and Banks**

The dependent variable is the share of defaulted credit over total credit in the province (columns 1-2) or in the overall bank loan portfolio (columns 3-5) in each year. $\text{Overconfidence}_{\text{Math}}$ 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). 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)	(2)	(3)	(4)	(5)
	Default Rate				
	Province		Bank-Province		
$\text{Overconfidence}_{\text{Math}}$	0.192**	0.218**	-0.076		
	(0.076)	(0.104)	(0.049)		
$\text{Overconfidence}_{\text{Math}}$ × Collateral			0.035**	0.034**	0.010*
			(0.017)	(0.015)	(0.006)
Collateral			-0.024**	-0.024**	
			(0.012)	(0.011)	
Area-Year FE	Y	Y	Y	Y	Y
Geographic Controls	-	Y	Y	-	-
Province FE	-	-	-	Y	Y
Bank-Year FE	-	-	-	-	Y
Observations	1616	1616	64923	64939	64923
R^2	0.219	0.277	0.046	0.086	0.758

Table A.15: **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. $\text{Overconfidence}_{\text{Math}}$ (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. South (Orig) is a dummy equal to one if at least one of the senior manager comes from a province in the South; Log(Age Manager) is average age of senior managers and Female Manager is a dummy equal to one if at least one of the senior managers is female. Other 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). 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	
$\text{Overconfidence}_{\text{Math}}$ (Orig)	0.751	0.905	-0.032	-0.105	-0.007	-0.004
	(0.988)	(0.900)	(0.220)	(0.275)	(0.019)	(0.020)
South (Orig)	0.119***	0.128***	0.030**	-0.003***	-0.003***	-0.002***
	(0.031)	(0.036)	(0.013)	(0.014)	(0.001)	(0.001)
Log(Age Manager)	-0.550***	-0.520***	-0.110***	-0.110***	0.006***	0.005***
	(0.048)	(0.043)	(0.012)	(0.012)	(0.001)	(0.001)
Female Manager	-0.082***	-0.075**	-0.012**	-0.011**	0.002**	0.001**
	(0.028)	(0.030)	(0.005)	(0.005)	(0.001)	(0.001)
Other manager charact.	Y	Y	Y	Y	Y	Y
Province FE	N	Y	N	Y	N	Y
Area-Year FE	N	Y	N	Y	N	Y
Industry-Year FE	N	Y	N	Y	N	Y
Observations	196148	196148	196148	196148	196148	196148
R^2	0.071	0.082	0.086	0.090	0.030	0.035