Corporate Overconfidence and Bank Lending

Filippo De Marco   Julien Sauvagnat   Enrico Sette*

January 26, 2022

Abstract

We study the role of banks in amplifying the economic impact of biases in managerial beliefs. For identification, we exploit plausibly exogenous variation in pupils' overconfidence across areas in Italy. Overconfident managers systematically overestimate future sales, and are more likely to default. Banks are more likely to deny credit to overconfident managers, but only for loans that cannot be easily collateralized. Results hold in a sample of movers (managers working in a different province from where they were born). Overconfident managers invest more when they borrow from collateral-based banks.

Keywords: overconfidence; business expectations; loan applications; borrower default; collateral requirements.
JEL: G41, G21

*Filippo De Marco: Bocconi University, IGIER, Baffi-Carefin and CEPR. email: filippo.demarco@unibocconi.it. Julien Sauvagnat: Bocconi University, IGIER, BIDSA, and CEPR. email: julien.sauvagnat@unibocconi.it. Enrico Sette: Bank of Italy. enrico.sette@bancaditalia.it. We are grateful to Christa Bouwman, Martin Brown, Claudia Custodio, Francesco D'Acunto, Ramona Dagostino, Kornelia Fabisik, Nicola Gennaioli, Mariassunta Giannetti, Yueran Ma and other seminar participants at AFA 2022, Bank of Italy, Barcelona GSE Summer Forum 2021, BI Oslo, Bocconi University, MoFiR Seminar, JEF seminar, SFS Cavalcade NA 2021, University of Bologna, University of Naples and Zurich Sustainable Banking Workshop for helpful comments and suggestions.

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 corporate overconfidence affects lenders (i.e. credit supply decisions), which is a key question to understand the economic impact of overconfidence.[2] After all, if banks deny credit to overconfident managers who want to raise external funds and increase the scale of their operations, the economic impact of corporate overconfidence might be limited.

Theoretical work highlights that credit markets may be characterised by excessive lending when some borrowers are overconfident about the future prospects of their firms (de Meza and Southey, 1996; de Meza, 2002). Manove and Padilla (1999) show that, when borrowers have biased beliefs about their projects, collateral requirements, differently from what happens in standard asymmetric information models, can reduce credit market efficiency by inducing lenders to lend to overconfident borrowers who then invest in value-destroying projects.[3] However, the intrinsic difficulty in empirically isolating the effects of corporate overconfidence from other confounding factors such as credit risk, together with data limitations on firms, banks and loan outcomes has made testing these theories a challenge. In this paper, we provide novel empirical evidence on how the impact of managerial overconfidence on corporate

[1] For example, Cooper et al. (1988) find that 68% of entrepreneurs perceive their odds of success as better than others in the same industry, while only 5% perceive their own chances as worse. The general tendency of people, and not just managers, to overestimate their chances of success is a robust findings in psychology. In economics, overconfidence refers 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.

[2] In this paper, *managerial overconfidence* and *corporate overconfidence* (or *borrowers' overconfidence*) refer to the same notion. We use this terminology in order to highlight that our focus is on understanding the implications of overconfidence of non-financial firms and their managers for banks' lending decisions, as opposed to the effect of *bank overconfidence* on their lending decisions.

[3] More generally, behavioral biases such as overconfidence may weaken the asymmetric-information rationale for government interventions in financial markets because they may turn policies beneficial to all agents into wealth transfers between agents (Sandroni and Squintani, 2007).

outcomes, such as investment, depends upon banks' credit supply decisions.

We begin by providing some stylized facts on the relationship between managerial biases and credit outcomes. To do this, we exploit confidential survey data on business expectations of Italian firms matched with loan-level data from the Bank of Italy credit registry.[4] We document that borrowers who systematically make positive forecast errors (i.e. who consistently forecast revenues above the realized ones) have a 44% higher probability of default compared to other firms. However, one important challenge for identification is that positive forecast errors, even if systematically correlated over time, might not necessarily reflect corporate overconfidence, but instead the occurrence of unexpected negative shocks that induce rational errors ("bad luck"). In addition, firm-level forecast errors may correlate with other firm unobservables that in turn affect firm performance.

To identify the effect of overconfidence on loan outcomes, we then construct plausibly exogenous variation across areas in Italy using the share of local students in the national education attainment test (INVALSI) who say that they find Mathematics easier than their classmates.[5] In line with prior work focusing on the role of historical or cultural factors, such as ethnicity, customs and local traditions, which are known to affect current beliefs (Guiso et al., 2004, 2016; D'Acunto et al., 2019; Michalopoulos and Xue, 2021), we consider overconfidence a local cultural trait and we hypothesize that pupils' overconfidence about their own ability in Math will also reflect the intrinsic overconfidence of local firms.[6] Using pupils' local overconfidence as a proxy for local borrowers' overconfidence allows us to achieve

[4]There are two common ways to measure managerial overconfidence: late option-exercise and popular press characterizations (Malmendier and Tate, 2005, 2008) or positive forecast errors (Landier and Thesmar, 2008; Ben-David et al., 2013; Otto, 2014). We rely on the latter because most of the firms in our sample are not listed. Moreover, Hribar and Yang (2016) show that the two measures are similar: option- or press-based overconfident managers are more likely to issue over-optimistic earnings forecasts.

[5]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). Indeed, consistent with the presence of a "better-than-average" effect, 72% of Italian students say they find Math easier than their classmates. See Section 3.4 for further details about the construction of this measure.

[6]Understanding the origins of local differences in overconfidence is outside the scope of this paper. A related question is whether overconfidence relates to the areas in which people are born and raised, or to the areas in which they reside. While we do not take a stand on this question, we note that around 70% of executives of Italian firms live and work in the same province where they were born. We exploit the presence of movers in robustness analysis in Section 8.

identification in that, unlike business forecast errors, students' self-reported ability is plausibly unrelated to contemporaneous economic shocks.

We find a robust relationship between pupils' overconfidence and the likelihood of local firms to issue overly-optimistic forecasts. 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 forecasts' min-max interval. Our approach therefore isolates overplacement about the firm's future prospects from other determinants of beliefs, such as dispositional optimism (Puri and Robinson, 2007) or miscalibration (Ben-David et al., 2013).

Our measure of overconfidence may be correlated with other characteristics of the local economy or with the quality of local institutions. To address this concern we control for a vector of local characteristics, such as: attitudes toward trust and risk from the Global Value Survey (Falk et al., 2018), local GDP per capita, court efficiency, and a (time-varying) "South" dummy.[7] In this respect, we also find that pupils' overconfidence is not correlated with local social preferences, other than a weakly significant correlation with trust, which is fully captured by the South dummy. The non-significant correlation lends further support to the idea that our measure of overconfidence is not capturing other local cultural traits.

We then use our measure to isolate the effect of local borrowers' overconfidence on credit outcomes. We confirm our initial evidence on defaults and overconfidence: firms located in overconfident areas have a higher likelihood of default, and pay higher interest rates on unsecured credit lines.[8] We then turn to the implications of borrowers' overconfidence for the allocation of bank credit. For this, we exploit loan application data and estimate whether overconfident borrowers are more likely to be denied credit. Consistent with the notion that banks exert a disciplinary effect, we find that loan applications from first-time borrowers in

[7]Southern Italy is the least developed area in the country and it suffers from a weaker enforcement of creditor rights. See for example Guiso et al. (2004) on the North-South divide.

[8]We focus on unsecured credit lines because these are a homogeneous product that allows a clear comparison across banks and borrowers. The extra default risk is correctly priced in loan terms, allowing banks to break-even on average. However, this does not imply that credit is *not* misallocated. As shown in the model presented in the Online Appendix B, where all banks break-even by definition under perfect competition, credit is still misallocated, even if correctly priced, because overconfident borrowers invest in NPV$<$0 projects.

more overconfident areas are less likely to be accepted, and when accepted, borrowers obtain smaller loans.

Next, we test the key theoretical prediction that banks' collateral requirements shape credit allocation towards overconfident borrowers (Manove and Padilla, 1999). Using bank survey data, we show 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.[9] The specifications include firm-year fixed-effects, indicating that banks with different collateral requirements have different approval rates for the same firm in the same year. Since excessive reliance on collateral may weaken bank incentives to screen borrowers and their going-concern value (Manove et al., 2001; Berger and Udell, 2006; Goel et al., 2014; Ma and Kermani, 2021), we stress that our results are not simply driven by firm risk: high-collateral banks are not lending more to firms with low credit quality.[10] Taken together, these findings are consistent with the notion that banks' collateral provision reduces the efficiency of the credit market when the corporate sector is prone to excessive overconfidence.

Finally, we explore the implications of overconfidence and collateral for corporate investment. Previous work has found that investment is affected by managerial overconfidence: Goel and Thakor (2008) show theoretically that overconfident managers invest more than rational managers and Malmendier and Tate (2005), Ben-David et al. (2013) provide empirical evidence in this direction. We also find that overconfident borrowers invest more than others, but our novel contribution is to show this effect is amplified by the collateral lending channel: the sensitivity of investment to overconfidence is higher for firms that borrow from banks that rely on collateral-based lending.

To bolster the identification strategy, we hypothesize that the behavior of managers who

[9] Similarly, the likelihood of being denied credit is reduced for overconfident firms in industries with more tangible fixed assets, which can be more easily used as collateral by banks.

[10] In robustness tests we include collateral×credit score dummies×year fixed-effects, to fully absorb unobserved heterogeneity of credit allocation by high-collateral banks. Overconfident managers may be risky because they innovate more (Galasso and Simcoe, 2011; Hirshleifer et al., 2012); however more than 99% of the small firms in our sample do not have patents, thus innovation is unlikely to play a role in our setting.

moved to work in another area is still affected by the overconfidence of the province they were born in. Thus in robustness tests we restrict the sample to "movers" and we include fixed effects for the location of the firm, so that the coefficient of interest is identified from the comparison of managers who were born in different areas but currently work in the same area (Guiso et al., 2004, 2021). All the results remain similar to the baseline estimates, indicating that potential biases induced by unobserved local characteristics are already taken into account by the geographic controls. Importantly, we do not find that overconfident movers join ex-ante riskier firms, which addresses the concern that the "movers" estimates could reflect endogenous matching between overconfident managers and risky firms.

We also run a series of empirical tests to address the concern that our results are driven by local bank overconfidence. First of all, we note that there are no theoretical reasons to expect that bank overconfidence affects lending decisions to firms in any particular direction.[11] Second we repeat the analysis (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. Our estimates are virtually unchanged in both cases. Thus, potential differences in the behavior of local branches within the same bank do not have a material impact on our findings.

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 (Landier and Thesmar, 2008; Malmendier et al., 2011), risk-taking and innovation (Galasso and Simcoe, 2011; Hirshleifer et al., 2012), and firm value (Malmendier and Tate, 2008; Barrero, 2021).[12] There is also a fast-growing literature studying the implications of lenders' biased beliefs for

[11] Bank overconfidence conceptually means that loan officers have biased beliefs about their own ability, not about the quality of the projects of local firms applying for a loan. An overconfident loan officer that overestimates her ability to screen borrowers may have either higher or lower acceptance rates.

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

the economy, especially in 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 overconfidence in the corporate sector affects credit outcomes and banks' balance sheets through a collateral channel.

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).[13] 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. (2019) 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. Our identification strategy allows us to test key theoretical predictions on how borrowers' overconfidence impacts bank credit supply and how collateral provision relaxes overconfident borrowers' credit constraints.

Finally, our empirical findings speak to a series of papers providing evidence on how bank lending practices (Jappelli and Pagano, 2002; Liberti, 2018; Liberti et al., 2016), and banks' collateral requirements shape credit outcomes. Theoretical work highlights that the effect of collateral requirements on the efficiency of capital markets is ambiguous and depends on the nature of the frictions at play between borrowers and lenders (Bester, 1985). For example, Manove et al. (2001) and Goel et al. (2014) show that a high value of collateral may weaken banks' incentive to screen. We provide novel empirical evidence on the distortionary effects of collateral requirements through borrowers' overconfidence, consistent with predictions in

[13]These models sometimes use the terminology "optimistic" for managers who overestimate the level of their firms' cash flows, and refer instead to "overconfidence" as the tendency to underestimate the volatility of their firms' cash flows (see e.g. Hackbarth, 2008), a notion that is referred to as miscalibration in other studies. In this paper "overconfidence" leads managers to overestimate the net-present-value of their future projects, thinking that these are better than their true quality.

Manove and Padilla (1999) and Bridet and Schwardmann (2020).

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

In the psychology literature, the term overconfidence refers to a variety of different concepts: 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 in Malmendier and Tate (2005, 2008).

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). This is because overconfidence leads managers to (wrongly) perceive negative net-present-value (NPV hereafter) projects as being profitable (Heaton, 2002).[14] How do lenders screen for overconfident borrowers? While de Meza and Southey (1996) assume that banks directly observe borrowers' overconfident traits, Manove and

[14]Note that managerial overconfidence differs from what prior work has referred to as empire-building. Empire-builders, like overconfident managers, may take on negative net-present-value projects, but, unlike the former, they do so intentionally.

Padilla (1999) work under the hypothesis that banks cannot differentiate among borrowers. While in adverse selection models lenders can discriminate between firms with projects of different qualities using a menu of contracts (Bester, 1985), this does not allow to screen for overconfident borrowers as by definition they are not conscious of their own biases. Instead, collateral requirements are shown to dilute lenders' discipline and exacerbate capital-market inefficiencies in the presence of overconfident borrowers.

In the Online Appendix B we provide a stripped down version of a model of bank lending to overconfident borrowers based on Manove and Padilla (1999) and Landier and Thesmar (2008). This allows us to derive simple predictions that will guide our empirical analysis in the rest of the paper. We expect 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 they are more likely to invest; (iii) when they do receive financing, they are more likely to default ex-post.

3 Data

We use different sources of information. We discuss each of these in more details below. The sample period for our empirical analysis is 2001-2017.

3.1 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.[15] 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.

3.2 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.

[15] 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.

3.3 Credit register

Detailed data on credit are obtained from the Italian Credit Register (CR). The CR is maintained by the Bank of Italy and collects information about loan applications from individual borrowers (including first-time borrowers) to each bank in Italy and tracks the amount of credit at the bank-firm level for credit exposures over €75,000.[16] For a subgroup of around 90 banks accounting for more than 80% of aggregate credit, the registry also collects data on the interest rate charged to each borrower by loan type. We focus on revolving credit lines (overdraft facilities) as they are a homogeneous, unsecured product across banks, whose interest rate can change at any point in time.[17] 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.[18] This is automatically recorded when firms are in liquidation or other bankruptcy proceedings. Thus, we measure borrower default rates by observing when the loan is classified as bad debt.

3.4 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 standardized test 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).[19]

Crucially for our purposes, we have access to a questionnaire where students are asked

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

[17] Interest rates are calculated as the ratio of the payment made in each year by the firm to the bank to the average amount of the loan used, as in Crawford et al. (2018).

[18] 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).

[19] 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. In terms of population, Italian provinces are about the size of US Metropolitan Statistical Areas (MSAs).

to report their beliefs about their own ability in Italian and 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, students who find Mathematics neither easier nor harder than their classmates, but equally easy, are probably not to be considered overconfident, but they are still likely to answer "no" to the above question. The presence of these students would lead us to overestimate the *level* of pupils' overconfidence in a given province.[20] 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".[21]

[20]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.

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

[INSERT TABLE 1 HERE]

Table 1 reports summary statistics for the different components of our final dataset. We will discuss the summary statistics of each dataset in the relevant section of the empirical analysis below.

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. Even though these bank-survey measures are only available for 2006, bank culture and business models are considered time-invariant (Fahlenbrach et al., 2012). 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.2). 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 Empirical Design

4.1 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 we measure corporate overconfidence as forecasts that exceed ex-post realized outcomes. In particular, we compute the sales growth forecast error as the difference between the firm's subjective forecast $F_t(\cdot)$ and future actual sales over current sales:

$$FE_{t+1|t} = F_t(SalesGr_{t+1}) - SalesGr_{t+1} \tag{1}$$

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. The forecast error is the sum of two components: a true error, denoted $E_t^{true}(\cdot)$ below, and a bias. In fact, without loss of generality we can rewrite the expression in (1) as:

$$FE_{t+1|t} = \underbrace{\left(E_t^{true}(SalesGr_{t+1}) - SalesGr_{t+1}\right)}_{\text{“rational error”}} + \underbrace{\left(F_t(SalesGr_{t+1}) - E_t^{true}(SalesGr_{t+1})\right)}_{\text{“bias”}}$$

The first component is a random variable with mean zero, i.e. the error that a rational firm would make. The second component is deterministic, and it is equal to zero only for rational firms. Conceptually, we think about overconfident borrowers as those with "bias"> 0, i.e. those that systematically overestimate future realizations.

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. A large fraction of firms (24%) make large, positive forecast errors in excess of 10 percentage points. We define these firms to be overconfident ($\mathbb{1}(FE_{t+1|t} > 0.1)$). A significant, yet smaller, fraction of firms (17%) makes large negative forecast errors ($\mathbb{1}(FE_{t+1|t} < -0.1)$). Consistent with Ma et al. (2019), we find that positive forecast errors are strongly persistent in the cross-section of firms: making a sales growth forecast error in excess of 10 percentage points in year t leads to a higher probability of making the same mistake in year $t+1$ to $t+4$ (see Table A.2 in the Online Appendix).

4.2 Firm forecast errors and default: a first pass

In this section, we ask whether overconfident borrowers are more likely to default on their debt. We focus on bank debt which represents the only form of external finance for the vast majority of the firms, mostly SMEs, in our sample. We measure default with the likelihood that in year $t+1$ the firm existing credit exposure is classified as bad debt by the bank. Figure 2 presents a scatter-plot of the relationship between forecast errors and default probabilities across all firms in the INVIND survey. We find that firms with positive forecast errors are indeed unconditionally more likely to default than other firms. Strikingly, the figure also shows a strong asymmetry between positive and negative forecast errors: the association between the forecast error and the probability of default is positive only for those with $FE_{t+1|t} > 0$, while it is flat for those for which $FE_{t+1|t} < 0$.[22] This suggests that the effect is not related to differences in forecasting ability across firms, but to overconfidence which in turn leads to risky corporate decisions.

Still, the relationship between default probability and forecast errors in Figure 2 may be the result of an omitted variable bias, for instance the occurrence of unexpected negative shocks that would lead firms to make rational errors and default at the same time. As a first pass to gauge the severity of this concern, we include here a variety of confounding factors that are expected to influence both default and forecast errors by running the following regression in the sample of INVIND firms:

$$Default_{i,j,t+1} = \beta_1 \mathbb{1}(FE_{i,t+1|t} > 0.1) + \beta_2 SalesGr_{i,t+1} + \gamma' X_{i,t} + \mu_{j,t} + \epsilon_{i,t} \quad (2)$$

where $Default_{i,j,t+1}$ is a dummy equal to one if the credit exposure by firm i in (2-digit) sector j is classified as bad debt in year $t+1$, and $\mathbb{1}(FE_{i,t+1|t} > 0.1)$ is a dummy that equals one for firms with positive forecast errors in excess of 10 percentage points. As control variables, we

[22] This asymmetry would also emerge in the model presented in the Online Appendix B if we were to consider credit outcomes to underconfident borrowers, defined as those that would interpret good signals as being bad. These borrowers would always find optimal to implement the Safe strategy, and therefore, they would not default ex-post.

include firms' contemporaneous realized sales growth between year t and $t+1$ ($SalesGr_{i,t+1}$), in order to isolate the effect of firms' forecasts on default from that of realized shocks. The vector $X_{i,t}$ includes controls for other firm characteristics such as lagged sales growth, the 3-year volatility of sales (as a measure of uncertainty of the forecast target), firm age, assets, profitability and firm Altman-Z credit score. $\mu_{j,t}$ are industry×year fixed-effects. We cluster standard errors at the firm level.

[INSERT TABLE 2 HERE]

We present the results in Table 2. First of all, controlling only for year fixed-effects, an overconfident borrower is 3.1 percentage points more likely to default. This is a large effect, since the unconditional probability of default in the INVIND sample is about 2.9% on average: overconfident borrowers are twice as likely to default than other firms. The effect is not driven by industry-time shocks, as the coefficient remains stable when we include industry-year fixed-effects in column (2). The effect is reduced to about one third, but remains highly statistically significant, when we include firm characteristics in column (3). As expected, negative future shocks, as measured by lower realized future sales, increase the probability of default, along with lower profitability and higher ex-ante credit risk. In the last column in which we fully control for the full set of credit score dummies interacted with year fixed-effects ($\mathbb{1}(CreditScore) \times Year$), the coefficient indicates that overconfident borrowers are 44% more likely to default than other firms.

4.3 Identification strategy

The evidence presented in the previous section suggests that overconfident borrowers are more likely to default. While informative, in order to credibly isolate the impact of borrowers' overconfidence on their probability to default, one needs to address the joint endogeneity of firm business expectations and default probabilities to economic shocks. For this, we construct a plausibly exogenous measure of local overconfidence using differences in pupils' self-declared ability in Mathematics relative to their classmates.[23]

We hypothesize that pupils' overconfidence about their own ability in Math will also reflect the intrinsic overconfidence of local borrowers. This is consistent 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. D'Acunto et al. (2019) show that households in counties where historical antisemitism was higher express lower trust in finance even today.

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:

$$Y_{i,j,p,t+1} = \beta \text{Overconfidence Math}_p + \lambda' X_p + \gamma' X_{i,t} + \mu_{j,t} + \epsilon_{i,t} \tag{3}$$

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 Overconfidence 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).[24] For example, students in the South are more overconfident in their ability in Math than their fellow students in the

[23] A similar strategy, using health rather than education outcomes, was proposed by Puri and Robinson (2007). They compare the individual self-assessed life expectancy from the Survey of Consumer Finance to that implied by statistical tables, and use it to study the implications of optimism for households' financial choices.

[24] 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. See Section 4.4 for a detailed description of these geographic controls.

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.

We present in Figure 3 the residuals of pupils' overconfidence after controlling for all the local geographic factors that we also include in the estimation of equation (3), i.e. the map shows the variation in pupils' overconfidence, net of local environmental factors, that we actually use in our regressions. While there are still some clusters of overconfidence after controlling for local geographic factors, there is significant cross-sectional variation within each macro-area. Furthermore, we find in the Online Appendix Table A.1 that the share of overconfident students is strongly persistent across different waves of the survey, and correlates well with two alternative measures of overconfidence from the INVALSI survey: (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 key results on credit and collateral requirements also hold if we use these measures of pupils' overconfidence.

4.4 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. We find in Figure 4 that 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 3. 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 4 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 3 HERE]

Since our measure of overconfidence varies at the local level, we need to control for potential confounding factors that may be correlated with overconfidence in the same area. We do so in column (2). First of all, given that pupils in southern regions tend to be more overconfident than those in the North, we control for a "South" dummy, for local economic development with the (log of) GDP per capita in the province, and for the inefficiency of law enforcement with the average number of days it takes to complete bankruptcy proceedings in the local courts. Second, we control for local preferences using the answers to the Global Value Survey on people's risk, trust and social preferences from Falk et al. (2018) which are available for 19 regions in Italy.[25] 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 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 say 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

[25]Table A.3 in the Online Appendix shows that pupils' overconfidence does not correlate with any local preference measure from Falk et al. (2018), 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). The non-significant correlation with local attitudes towards reciprocity, patience and risk taking lends further support to the idea that our measure of overconfidence is not capturing other cultural traits at the local level.

their own future performance and aggregate economic outcomes from SIGE (Coibion et al., 2019). The results are presented in Table 4.

[INSERT TABLE 4 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, future sales' forecasts are higher for firms expecting an improvement in their own business conditions and we find they do (Panel C). It is reassuring that the same firms give consistent answers in two different surveys. 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.4 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 $\mathbb{1}(FE > 0.1)$ (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 Results

5.1 Loan default

We now estimate the effect of local borrowers' overconfidence on credit outcomes. First, we re-assess our initial evidence about the relationship between corporate overconfidence and default. In order to do this, we estimate Equation 3 in which the dependent variable Y_i is the 1-year default probability of firm i.

[INSERT TABLE 5 HERE]

Results on loan defaults are presented in Table 5. 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, i.e. the weaker enforcement of creditor rights in the South of Italy, as we are controlling for "South"-year fixed-effects and a host of other geographic factors (including the efficiency of law enforcement, and local attitudes towards trust).[26] 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).

5.2 Loan rates

Having established that local overconfidence affects default, and that this matters over and above quantitative information contained on firm balance sheets or past performance, we then ask whether banks price this risk component in their loan terms. We restrict our attention to revolving credit lines, which represent around a third of total bank lending to firms in our sample. Revolving credit lines are ideal for our purposes because they are a homogeneous

[26]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.5 in the Online Appendix).

product across borrowers, which facilitates the comparison of the rates paid by overconfident and non-overconfident borrowers, that could be otherwise confounded by differences in other loan characteristics. In fact, revolving credit lines do not have a pre-specified duration and are unsecured, hence differences in loan maturity or collateral cannot influence the differences in rates (Crawford et al., 2018). Moreover, the bank can change the interest rate on a revolving credit line at any time, as if it were a new loan.

[INSERT TABLE 6 HERE]

The results are presented in Table 6. We find a positive and statistically significant association between local overconfidence and the rates paid on unsecured credit lines. 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 on NPLs for unsecured credit lines in Italy in 2017 is 22% and the coefficient of optimism on default is 0.19 (see column (4) of Table 5), a simple back of the envelope calculation suggests that the coefficient on the loan rate for banks to break-even should be around $0.19 \times 0.78 = 14.8$. This is remarkably close to the estimated coefficients from Table 6, which are around 14.7. This is consistent with the predictions of the model presented in the Online Appendix B with sophisticated banks that are able to observe borrowers' overconfidence. [27]

Still, even though banks break-even on average when lending to overconfident borrowers, this does not mean that credit is *not* misallocated. Indeed in our model, where all banks break-even by definition under perfect competition, credit is still misallocated, because overconfident borrowers may invest in negative NPV projects, even if they receive a bad signal about their project. Higher recovery rates for banks in case of firms' default - driven for instance by higher collateral requirements - dilute lenders' disciplinary effects on overconfident borrowers

[27] The result is also consistent with models such as Manove et al. (2001) and Inderst and Mueller (2006) who assume that lenders, when screening projects, have better private information about borrowers' types than the borrowers themselves.

by lowering the interest rates that they charged to these firms. This in turn exacerbates credit markets' inefficiencies.

5.3 Loan applications and acceptance

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 7 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.[28] Table 7 reports the results. We first investigate whether overconfident borrowers are more likely to post loan applications compared to other firms. The effect of overconfidence on credit demand is ambiguous: on the one hand, overconfident borrowers may be inclined to ask for credit because they believe 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). As a result of this contrasting forces, our results in Panel A indicate that overconfident borrowers do not show a statistically different demand for credit.

We then look at acceptance rates of applications (Panel B of Table 7) from overconfident borrowers, and in the amount of credit granted when the application is accepted (Panel C). The point estimates 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 0.73 percentage points, i.e. 3% compared to the mean. The results are consistent with the notion that banks exert a disciplinary effect on overconfident borrowers and with the observed pricing of loans to overconfident borrowers: since these are riskier, they are credit constrained when they apply for a loan and when they obtain credit they are charged more

[28] 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, similar to Jiménez et al. (2014), in order to use firm-year fixed-effects in the estimation.

than other similar firms. We stress however that overconfidence is different from standard credit risk in that overconfident borrowers engage in NPV<0 projects even when they receive a bad signal about the quality of their project. Moreover, given the extensive set of credit score dummies interacted with year fixed effects, the impact of overconfidence we identify in the data is over and above that of credit risk.

Are our results biased by differences in local banks' behavior? 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 include bank-year fixed-effects in all the specifications with the loan acceptance rate. This ensures that bank-time specific variation, including bank overconfidence, does not affect our results. Second, while our measure could in principle be capturing differences in local loan officers' overconfidence (as opposed to borrowers' overconfidence), there are no theoretically clear reasons for why bank overconfidence should affect lending decisions to firms in a way that would confound our estimates. Indeed, if local loan officers are overconfident, conceptually this means that they have biased beliefs about their own ability to evaluate firms' projects, not about the quality of the projects per se. Local loan officers which are overconfident in their ability to screen borrowers are ex-ante equally likely to reject or accept applications from local firms.

Finally, given that unobserved differences in local loan officers' behavior across Italian areas could be in principle a source of bias in our regressions even with bank-year fixed-effects, 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.6 in the Online Appendix. Reassuringly, our estimates are virtually unchanged in both 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 banks' behavior across low versus high overconfidence areas is also addressed by the tests that we run in Section 8 on the sample of managers who moved from their province of birth to work for firms in other provinces, in which 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 theoretical prediction that collateral requirements relax financial constraints for overconfident borrowers and lead them to overborrow (see the model in Online Appendix B for further details). In our main test, 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. We also test below whether the likelihood of being denied credit for an overconfident borrower is reduced in industries with more tangible fixed assets (measured using the ratio of property, plant and equipment over total assets at the 2-digit industry level), which can be more easily used as collateral by banks. Formally, we estimate the following equation:

$$\begin{aligned} Accept_{i,b,t} = {} & \beta_1 \text{Overconfidence MATH}_p + \beta_2 \text{Overconfidence MATH}_p \times Collateral_b + \\ & \lambda Log(Dist_{i,b}) + \mu_{i,t} + \mu_{b,t} + \epsilon_{i,b,t} \end{aligned} \tag{4}$$

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.[29] $Collateral_b$ is the importance of collateral from the organizational survey 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. In robustness tests we use the fraction of tangible over total assets at the sector level as an alternative measure of collateral importance. 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 Overconfidence MATH_p and Collateral_b is positive and statistically significant. Importantly, since we include firm-year fixed-effects (Jiménez et al., 2014), the interaction 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 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. We thus augment our baseline specification interacting pupils' overconfidence with three key banks' characteristics: size, leverage and the

[29] A loan application is defined to be accepted at time t if there is a new firm-bank relationship that is formed within a quarter from the filing of the loan application. We obtain identical results if we use as dependent variable the amount of ln(Credit) when the application is accepted, 0 otherwise.

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 Overconfidence MATH$_p$ and Collateral$_b$ remains virtually unchanged.[30]

Credit Risk. One may also wonder 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. Indeed, Manove et al. (2001) and Goel et al. (2014) show 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; Ma and Kermani, 2021). First of all, we note that overconfidence is different from standard credit risk in that risky firms do not invest in negative NPV projects when they receive a bad signal. Second, to ensure that our results do not depend on the interaction between collateral banks and credit risk, in column (4) of Table 8 we include the interaction of Collateral$_b$ and the firm credit score. We find that the coefficient is not significant, i.e. high collateral banks are not more likely to lend to ex-ante riskier firms in general, and the coefficient on the interaction of interest remains unchanged. Moreover, 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 to overconfident firms, not to ex-ante riskier firms.

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 SMEs and not large listed firms like Compustat (Hirshleifer et al., 2012). We conclude that innovation is unlikely to play a role in

[30] We also explore whether other survey factors drive bank lending decisions in Table A.7 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.

our setting.

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.8 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.

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.9. Specifically, we run the same specification as in Equation 4 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 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 decrease in acceptance rate of about 5% compared to the mean, whereas those in industries with 100% of the assets being tangible have an increase in the acceptance rate by about 5%.

Robustness to other geographic factors. There is the possibility that what drives the correlation is not really overconfidence but correlated province-level factors such as geographical differences in economic development or the quality of contract enforcement. We thus augment our baseline specification with the interaction of collateral requirements with 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.10. Reassuringly, in all specifications, the coefficient on the interaction term remains positive and statistically significant.

Aggregate Defaults. Are the higher default rate associated to borrowers' overconfidence quantitatively large enough to explain the distribution of non-performing loans in the cross-section of banks? 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.11. 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 5. We then explore which banks are driving the increase in defaults in those areas by expanding the dataset at the bank-province level. We find 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. These findings indicate that corporate overconfidence matters for default rates and banks' balance sheets in the aggregate.

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 the allocation of credit by collateral-based banks affects the corporate decisions made by overconfident borrowers. This is a crucial mechanism to understand the economic impact of overconfidence. Since collateral-based lending banks are more inclined to lend to overconfident firms, access to bank credit may further increase the (over-)investment made by overconfident managers.

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 firms 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 columns (1) and (2) that corporate investment is sensitive to local pupils' overconfidence, even after controlling for other firm characteristics. 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). 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 corporate overconfidence depends on whom they 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 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 columns (3) and (4) that the higher sensitivity of investment to overconfidence is entirely driven by collateral-based banks: overconfident managers that borrow more from banks which value collateral have higher investment rates. Notably, borrowers of high-collateral banks who are not overconfident actually have lower investment rates, consistent with the result in Table 8 that these banks actually restrict credit to non-overconfident borrowers. 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.

Finally, we show that the higher investment sensitivity of overconfident borrowers is not due to credit risk: in column (5) of Table 9 we include the interaction of Collateral$_{f,t}$ and the firm credit score. We find that firms with higher credit score (i.e. riskier) that borrow from high-collateral banks invest less and, more importantly, the coefficient on the interaction of interest, Collateral$_{f,t}$ $\times$ Overconfidence MATH$_p$, remains unchanged. Moreover, we include an exhaustive set of Collateral$_b$$\times$ credit score dummies $\times$ year fixed-effects in column (6), and again our coefficient of interest is unchanged.

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.[31] Most firms with movers (75%) are located in the north of the country, consistent with the fact that internal migration is mostly a South to North phenomenon. We acknowledge that moving is not random and one may worry that overconfident managers match with 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.12 in the Online Appendix).

We then re-estimate all our 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, acceptance rate by banks that value collateral more and corporate investment. Reassuringly, in all these specifications, the coefficients on our proxy for

[31] 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 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).

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 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 overconfidence in the corporate sector. Our identification 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 document that firms in overconfident areas hold favorable views about their own business, not the economy in general, and find that they are more likely to default on their existing loans. We then show that banks are more likely to deny credit to firms in overconfident areas, 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. Moreover, 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. Our findings shed light on the instrumental role of banks in shaping how managers' overconfidence affect economic outcomes.

References

Adam, Tim, Valentin Burg, Tobias Scheinert, and Daniel Streitz, "Managerial Biases and Debt Contract Design: The Case of Syndicated Loans," *forthcoming, Management Science*, 2019.

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

Barrero, Jose Maria, "The Micro and Macro of Managerial Beliefs," *Journal of Financial Economics (forthcoming)*, 2021.

Ben-David, Itzhak, John R. Graham, and Campbell R. Harvey, "Managerial Miscalibration," *The Quarterly Journal of Economics*, 09 2013, *128* (4), 1547–1584.

Berger, Allen N. and Gregory F. Udell, "A more complete conceptual framework for SME finance," *Journal of Banking & Finance*, November 2006, *30* (11), 2945–2966.

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

Bester, Helmut, "Screening vs. Rationing in Credit Markets with Imperfect Information," *American Economic Review*, 1985, *75* (4), 850–55.

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

Bridet, Luc and Peter Schwardmann, "Selling Dreams: Endogenous Optimism in Lending Markets," *Working Paper*, 2020.

Cain, Carol, Mei Feng, and Douglas Skinner, "Does Earnings Guidance Affect Market Returns? The Nature and Information Content of Aggregate Earnings Guidance," *Journal of Accounting and Economics*, 2007, *44*, 36–63.

Carlana, Michela, "Implicit Stereotypes: Evidence from Teachers' Gender Bias," *The Quarterly Journal of Economics*, 03 2019, *134* (3), 1163–1224.

Carvalho, Daniel, Janet Gao, and Pengfei Ma, "Loan Spreads and Credit Cycles: The Role of Lenders' Personal Economic Experiences," 2021. Working Paper.

Coibion, Olivier, Yuriy Gorodnichenko, and Tiziano Ropele, "Inflation Expectations and Firm Decisions: New Causal Evidence," *The Quarterly Journal of Economics*, 09 2019, *135* (1), 165–219.

Cooper, Arnold C., Carolyn Y. Woo, and William C. Dunkelberg, "Entrepreneurs' perceived chances for success," *Journal of Business Venturing*, 1988, *31* (2), 97–108.

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

Crawford, Gregory, Nicola Pavanini, and Fabiano Schivardi, "Asymmetric Information and Imperfect Competition in Lending Markets," *The American Economic Review*, 2018, *108* (7), 1659–1701.

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

_ **and Clive Southey**, "The Borrower's Curse: Optimism, Finance and Entrepreneurship," *The Economic Journal*, 1996, *106* (435), 375–386.

Degryse, Hans and Steven Ongena, "Distance, Lending Relationships, and Competition," *Journal of Finance*, 02 2005, *60* (1), 231–266.

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

Fahlenbrach, Rüdiger, Robert Prilmeier, and René M. Stulz, "This Time Is the Same: Using Bank Performance in 1998 to Explain Bank Performance during the Recent Financial Crisis," *Journal of Finance*, December 2012, *67* (6), 2139–2185.

Falk, Armin, Anke Becker, Thomas Dohmen, Benjamin Enke, David Huffman, and Uwe Sunde, "Global Evidence on Economic Preferences," *The Quarterly Journal of Economics*, 05 2018, *133* (4), 1645–1692.

Fecht, Falko and Regina Opaleva, "Managerial Overconfidence and Access to Funding: Do Banks Help Managers to Avoid Investment Mistakes?," 2019.

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

Gervais, Simon, J. B. Heaton, and Terrance Odean, "Overconfidence, Compensation Contracts, and Capital Budgeting," *Journal of Finance*, 2011, *66* (5), 1735–1777.

Goel, Anand and Anjan Thakor, "Overconfidence, CEO Selection and Corporate Governance," *Journal of Finance*, 2008, *63* (5), 2737–2784.

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

Greenwood, Robin and Samuel G. Hanson, "Issuer Quality and Corporate Bond Returns," *The Review of Financial Studies*, 2013, *26* (6), 1483–1525.

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

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

— , **Paola Sapienza, and Luigi Zingales**, "The Role of Social Capital in Financial Development," *American Economic Review*, June 2004, *94* (3), 526–556.

— , — , **and** — , "Long-Term Persistence," *Journal of the European Economic Association*, 2016, *14* (6), 1401–1436.

Hackbarth, Dirk, "Managerial Traits and Capital Structure Decisions," *Journal of Financial and Quantitative Analysis*, 2008, *43* (4), 843–881.

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

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

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

Hribar, Paul and Holly Yang, "CEO Overconfidence and Management Forecasting," *Contemporary Accounting Research*, March 2016, *33* (1), 204–227.

Inderst, Roman and Holger M. Mueller, "Informed Lending and Security Design," *Journal of Finance*, October 2006, *61* (5), 2137–2162.

Jappelli, Tullio and Marco Pagano, "Information sharing, lending and defaults: Cross-country evidence," *Journal of Banking & Finance*, 2002, *26* (10), 2017–2045.

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

Landier, Augustin and David Thesmar, "Financial Contracting with Optimistic Entrepreneurs," *The Review of Financial Studies*, 2008, *22* (1), 117–150.

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

Liberti, José María, "Initiative, Incentives, and Soft Information," *Management Science*, 2018, *64* (8), 3714–3734.

— , **Amit Seru, and Vikrant Vig**, "Information, Credit, and Organization," SSRN Working Paper Series, SSRN 2016.

Ma, Yueran and Amir Kermani, "Two tales of debt," *Working Paper*, 2021.

— , **Teodora Paligorova, and José-Luis Peydró**, "Expectations and Bank Lending," 2020.

— , **Tiziano Ropele, David Sraer, and David Thesmar**, "A Quantitative Analysis of Distortions in Managerial Forecasts," 2019. Working Paper.

Malmendier, Ulrike and Geoffrey Tate, "CEO Overconfidence and Corporate Investment," *Journal of Finance*, 2005, *60* (6), 2661–2700.

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

_ **and Stefan Nagel**, "Depression Babies: Do Macroeconomic Experiences Affect Risk Taking?," *The Quarterly Journal of Economics*, 02 2011, *126* (1), 373–416.

_ **, Geoffrey Tate, and Jon Yan**, "Overconfidence and Early-Life Experiences: The Effect of Managerial Traits on Corporate Financial Policies," *Journal of Finance*, 2011, *66* (6), 1687–1733.

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

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

Michalopoulos, Stelios and Melanie Meng Xue, "Folklore," *The Quarterly Journal of Economics*, 01 2021, *136* (4), 1993–2046.

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

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

Oster, Emily, "Unobservable Selection and Coefficient Stability: Theory and Evidence," *Journal of Business & Economic Statistics*, 2019, *37* (2), 187–204.

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

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

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

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.

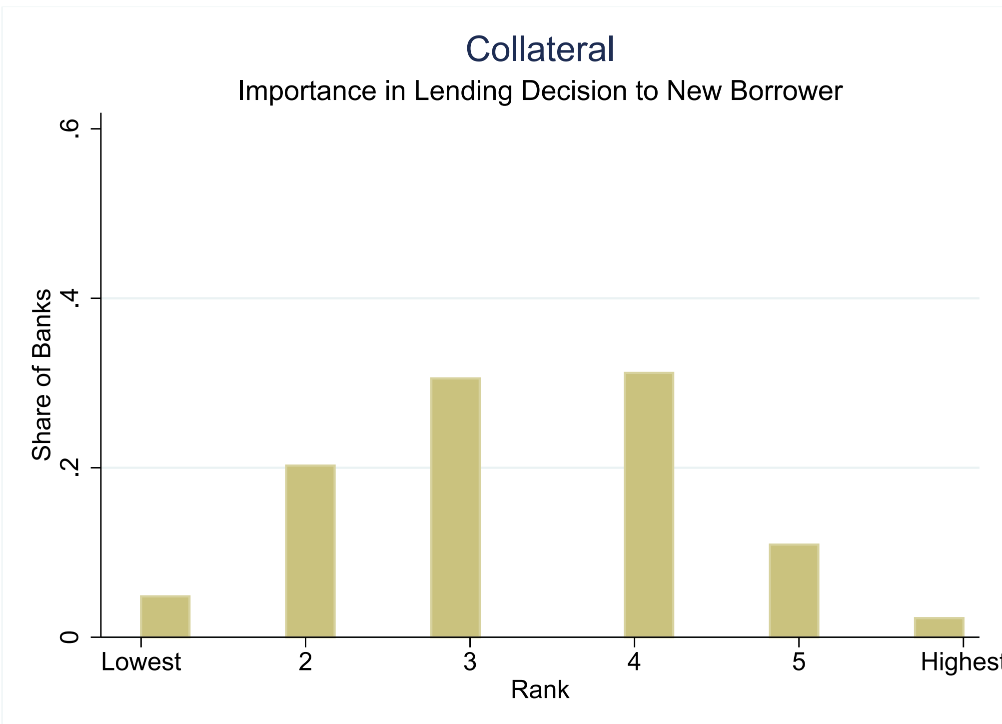


Figure 2: **Forecast Errors and Default**

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.

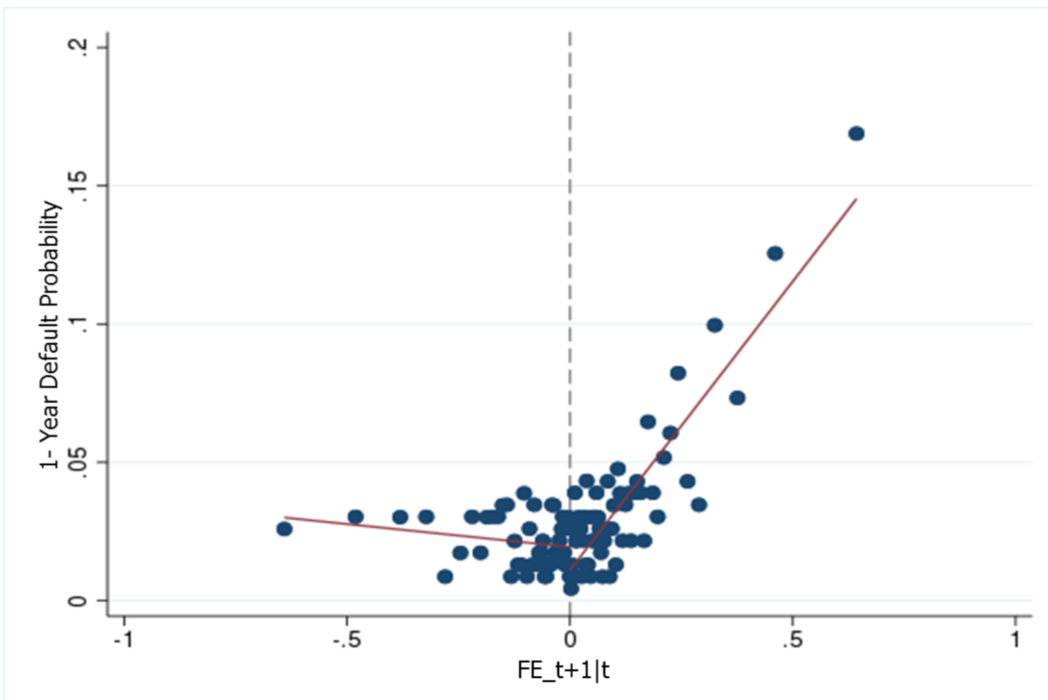


Figure 3: **Overconfidence in Mathematics**

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.

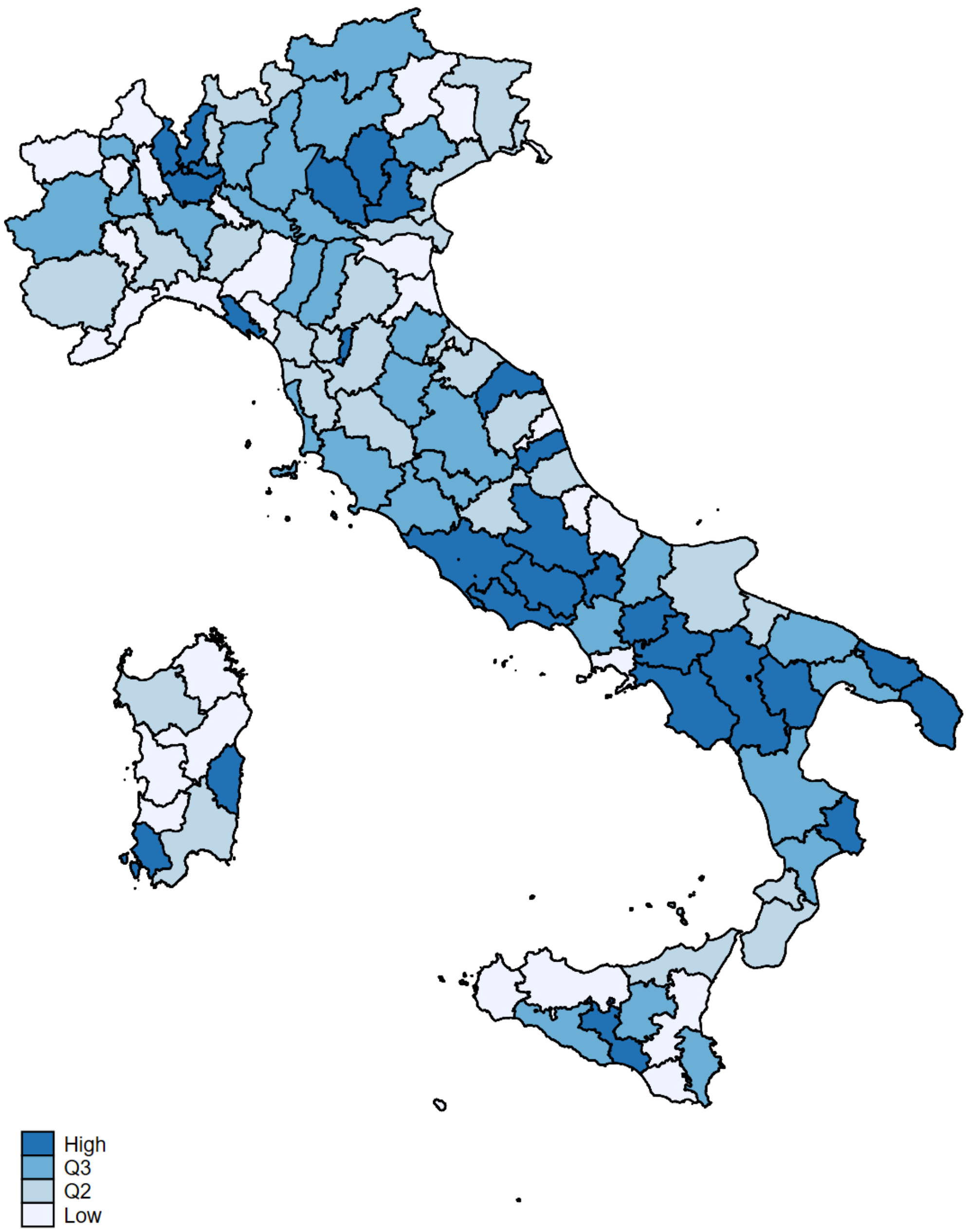
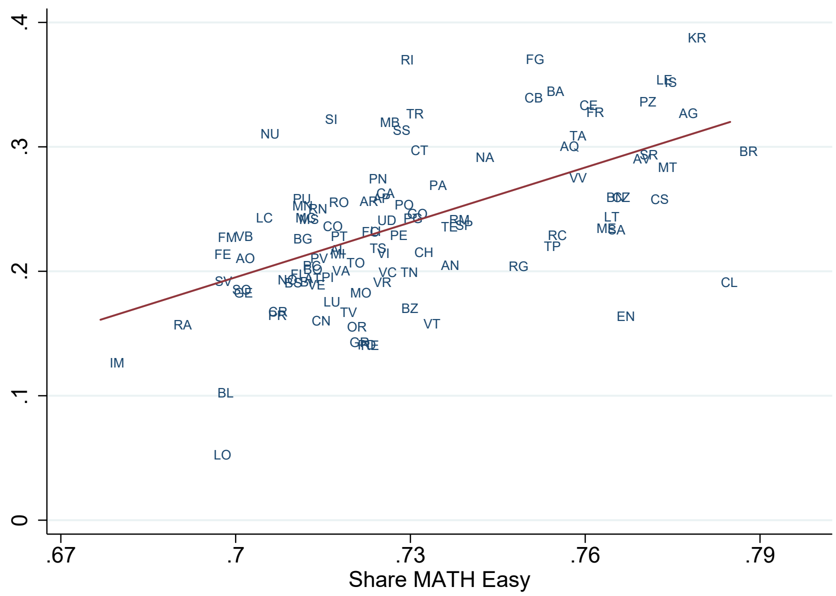


Figure 4: **Probability of Issuing Overconfident Forecast**

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 MATH



Panel B. Overconfidence ITA

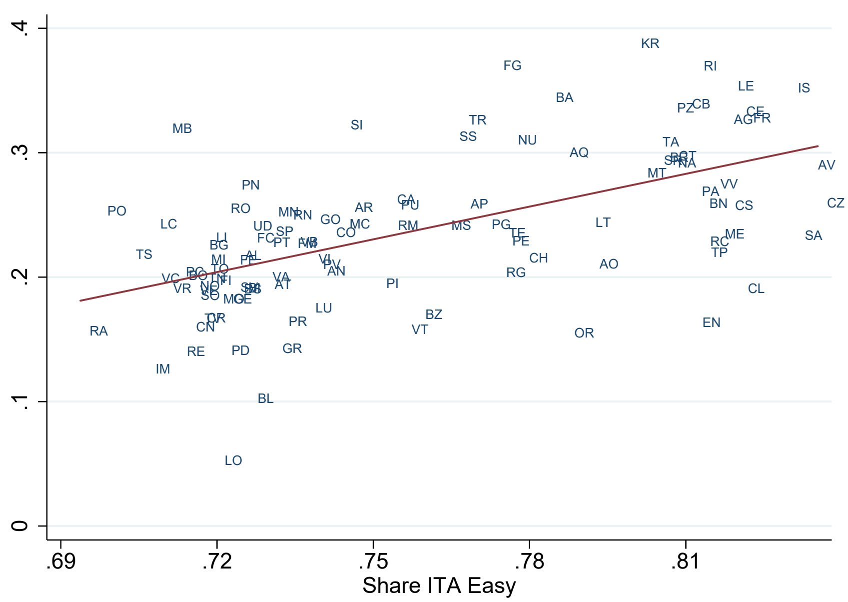


Table 1: **Summary Statistics**

This table presents the summary statistics for our data at the firm-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 regional level 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	0	1
Panel B. INVALSI, Province or Region characteristics						
Overconfidence MATH	110	0.727	0.025	0.677	0.722	0.782
Overconfidence ITA	110	0.756	0.040	0.697	0.744	0.833
GDP/Pop, €per capita (2006)	110	21904	5118	13827	22303	32287
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 (Credit line) in %	2136986	8.782	2.731	2.682	8.312	16.649
Credit Score	3214286	4.935	1.965	1.000	5.000	9.000
Firm Age (years)	3214286	17.269	12.730	3.000	14.000	60.000
Log(Firm Assets$_{t-1}$)	3214286	7.346	1.326	4.762	7.197	11.281
Sales Growth (t,t+1)	3214286	0.080	0.471	-0.790	0.018	3.024
Sales Growth Volatility	3214286	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: **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 (low risk) to 9 (high 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 3: **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. Overconfidence 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; a dummy equal to one if the firm is located in the south of Italy, including Sicily and Sardinia. 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)
	$\mathbb{1}(FE_{i,t+1\|t} > 0.1)$				
Overconfidence MATH	1.014***	0.864***	0.872***	0.679***	0.673***
	(0.147)	(0.217)	(0.217)	(0.206)	(0.202)
Firm Controls	Y	Y	Y	Y	Y
Year FE	Y	Y	-	-	-
Geographic Controls	N	Y	Y	Y	Y
South-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	0.280	0.284

Table 4: **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). Overconfidence 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). 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. Firm Own Business Condition Improves Next 3M			
Overconfidence 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			
Overconfidence 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	-	-	-
South-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 5: **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. Overconfidence 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). Credit Score is 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)
	$\mathbb{1}$(Bad Debt in t+1)			
Overconfidence MATH	0.194***	0.190***	0.189***	0.195***
	(0.043)	(0.042)	(0.040)	(0.040)
Sales Growth (t,t+1)			-0.009***	-0.008***
			(0.000)	(0.000)
Sales Growth (t-1,t)			-0.010***	-0.007***
			(0.000)	(0.000)
Sales Growth Volatility			0.005***	0.003***
			(0.000)	(0.000)
EBITDA/Assets			-0.006***	-0.001
			(0.001)	(0.001)
Log(Firm Age)			0.012***	0.012***
			(0.001)	(0.001)
Log(Firm Assets)			0.005***	0.005***
			(0.000)	(0.000)
Credit Score			0.010***	
			(0.000)	
Geographic Controls	Y	Y	Y	Y
South-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	0.025	0.037

Table 6: **Overconfidence and Loan Rates**

The dependent variable is the interest rate on revolving credit lines at the firm-year level. Overconfidence 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). Credit Score is Cerved Altman Z-score index, ranging from 1 (low risk) to 9 (high risk). 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)
	Revolving Credit Line Rate			
Overconfidence MATH	15.624***	14.961***	14.746***	14.741***
	(4.162)	(4.024)	(4.013)	(4.024)
Credit Score			0.045**	
			(0.022)	
Geographic Controls	Y	Y	Y	Y
Firm Controls	N	N	Y	Y
South-Year FE	Y	Y	Y	Y
Industry-Year FE	N	Y	Y	Y
$\mathbb{1}$(Credit Score)-Year FE	N	N	N	Y
Observations	2136986	2136986	2136986	2136986
R^2	0.027	0.035	0.037	0.039

Table 7: **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. Overconfidence 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: credit score, 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)			
Overconfidence MATH	0.027	0.039	0.199	0.201
	(0.344)	(0.311)	(0.266)	(0.266)
Observations	6450953	6450953	6450953	6450953
R^2	0.067	0.089	0.171	0.174
	Panel B. $\mathbb{1}$(Loan Application Accepted)			
Overconfidence MATH	-0.249**	-0.237**	-0.265**	-0.292***
	(0.106)	(0.104)	(0.110)	(0.106)
Observations	848131	848131	848131	848131
R^2	0.037	0.044	0.050	0.056
	Panel C. =Ln(Credit) if Accepted, 0 Otherwise			
Overconfidence MATH	-3.441**	-3.206**	-3.397**	-3.748***
	(1.340)	(1.278)	(1.363)	(1.308)
Geographic Controls	Y	Y	Y	Y
Bank-Year FE	Y	Y	Y	Y
Firm Controls	N	N	Y	Y
South-Year FE	Y	Y	Y	Y
Industry-Year FE	N	Y	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 8: **Overconfidence, Collateral and Credit Supply**

The dependent variable is a dummy equal to one if the application is accepted. Overconfidence 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)
	$\mathbb{1}$(Loan Application Accepted)				
Overconfidence MATH×Collateral	0.265***	0.368***	0.405***	0.403***	0.405***
	(0.094)	(0.102)	(0.108)	(0.107)	(0.105)
Collateral	-0.189***				
	(0.070)				
Credit Score×Collateral				-0.001	
				(0.001)	
Overconfidence MATH×Capital			0.048	0.047	0.052
			(0.044)	(0.042)	(0.044)
Overconfidence MATH×NPL/Assets			0.040	0.040	0.041
			(0.031)	(0.031)	(0.031)
Overconfidence MATH×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**

The dependent variable is the firm-level yearly investment rate, i.e. the change in fixed-assets over lagged fixed assets. Overconfidence 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). 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)	(6)
	Investment Rate					
Overconfidence MATH	0.301***	0.206***	0.123*	0.007	0.001	0.007
	(0.058)	(0.050)	(0.067)	(0.064)	(0.062)	(0.064)
$\text{Collateral}_{f,t}$			-0.071***	-0.109***	-0.106***	
			(0.010)	(0.010)	(0.011)	
Overconfidence MATH× $\text{Collateral}_{f,t}$			0.091***	0.128***	0.132***	0.130***
			(0.014)	(0.014)	(0.014)	(0.014)
Credit Score × $\text{Collateral}_{f,t}$					-0.001***	
					(0.001)	
Geographic controls	Y	Y	Y	Y	Y	Y
South-Year FE	Y	Y	Y	Y	Y	Y
Industry-Year FE	Y	Y	Y	Y	Y	Y
$\mathbb{1}$(Credit Score)-Year FE	N	Y	N	Y	Y	-
Collateral-$\mathbb{1}$(Credit Score)-Year FE	N	N	N	N	N	Y
Firm Controls	N	Y	N	Y	Y	Y
Observations	3075965	3075965	3075965	3075965	3075965	3075965
R^2	0.013	0.034	0.016	0.035	0.0354	0.0350

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 interest rate on revolving credit lines in column (3); a dummy equal to one if the application is accepted in columns (4) and the firm-level yearly investment rate in column (5). Overconfidence 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)
	$\mathbb{1}(FE_{i,t+1\|t} > 0.1)$	Default	Loan Rate	$\mathbb{1}$(Accepted)	Investment
Overconfidence MATH (Orig)	0.815**	0.108**	2.949*		-0.128*
	(0.352)	(0.043)	(1.616)		(0.074)
Overconfidence MATH (Orig) $\times$ Collateral				0.301***	0.104***
				(0.086)	(0.025)
South (Orig)	-0.019	0.005***	0.174***		0.004**
	(0.14)	(0.002)	(0.064)		(0.02)
Log(Age Manager)	-0.027	-0.007***	-0.160		-0.049***
	(0.021)	(0.002)	(0.108)		(0.003)
Female Manager	-0.006	0.001	0.008		-0.005***
	(0.008)	(0.001)	(0.043)		(0.001)
Province FE	Y	Y	Y	-	Y
South-Year FE	Y	Y	Y	-	Y
Other manager charact.	Y	Y	Y	-	Y
Industry-Year FE	Y	Y	Y	-	Y
$\mathbb{1}$(Credit Score)-Year FE	Y	Y	Y	-	Y
Firm-Year FE	N	N	N	Y	N
Bank-Year FE	N	N	N	Y	N
Overconfidence$\times$Bank charact.	N	N	N	Y	N
Observations	17285	634579	448020	163080	590536
R^2	0.333	0.043	0.032	0.500	0.036

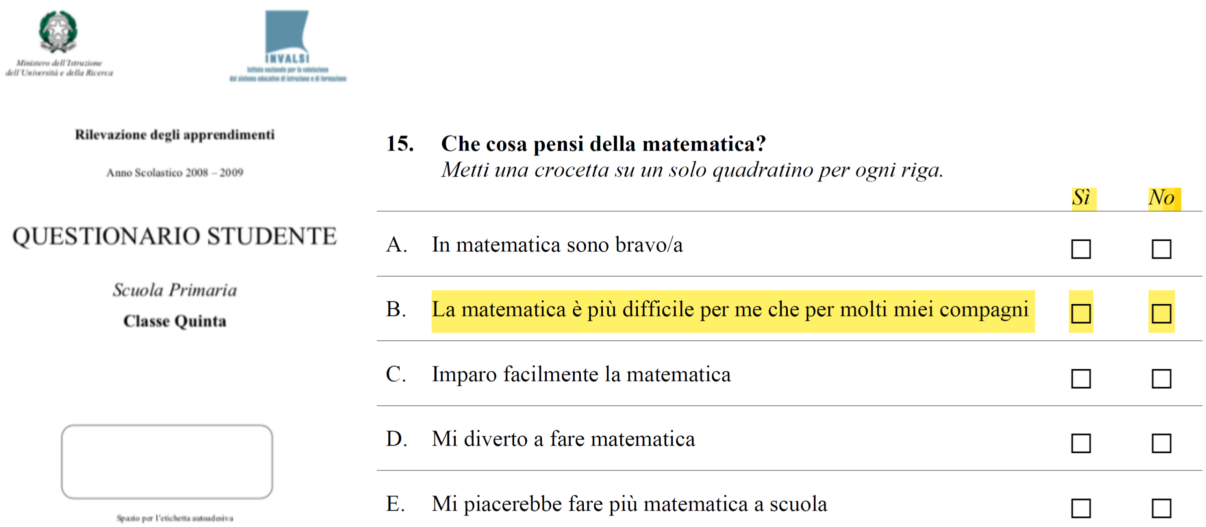
Online Appendix

Corporate Overconfidence and Bank Lending

This Online Appendix includes a series of additional Figures and Tables (Appendix A), and presents a simple model of bank lending (Appendix B).

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: **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: **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. Overconfidence MATH 2009 is the share of students who find Mathematics easier than their classmates in 2009; 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. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)
	Overconfidence MATH 2012	Overconfidence MATH 2009-2012	
Overconfidence MATH 2009	0.711***		
	(0.054)		
Overconfidence ITA		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.2: **Persistence in Forecast Errors**

The dependent variable is a dummy equal to one if the firm forecast error on future sales growth made in year τ, from $t+1$ to $t+4$, exceeds 10 percentage points, 0 otherwise. $\mathbb{1}(FE_{t>0.1})$ is the same dummy in year t. 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)
	$\mathbb{1}(FE_\tau > 0.1)$			
	$\tau = t+1$	$\tau = t+2$	$\tau = t+3$	$\tau = t+4$
$\mathbb{1}(FE_t > 0.1)$	0.167***	0.116***	0.143***	0.141***
	(0.009)	(0.009)	(0.009)	(0.008)
Year FE	Y	Y	Y	Y
Observations	19460	19460	19460	19460
R^2	0.105	0.091	0.097	0.097

Table A.3: **Correlation of Overconfidence with Risk, Time, and Social 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 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.4: **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 MATH	-0.053	0.057	0.048	0.033	0.031
	(0.088)	(0.134)	(0.135)	(0.134)	(0.132)
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 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	-	-	-
South-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 ITA	0.510***	0.497***			
	(0.132)	(0.130)			
MATH good but below median			0.512***	0.495***	
			(0.215)	(0.214)	
Firm Controls	Y	Y	Y	Y	
South-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.5: **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. Overconfidence 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). 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)			
Overconfidence MATH	0.226***	0.209***	0.190***	0.201***
	(0.054)	(0.054)	(0.048)	(0.050)
Observations	3530830	3530830	3530830	3530830
R^2	0.005	0.008	0.039	0.054
Panel B.	$\mathbb{1}$(Bad Debt in t+3)			
Overconfidence MATH	0.261***	0.234***	0.193***	0.208***
	(0.069)	(0.069)	(0.060)	(0.062)
Geographic Controls	Y	Y	Y	Y
Firm Controls	N	N	Y	Y
South-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.6: **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 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.	𝟙(Loan Application Accepted)		
Overconfidence MATH	-0.349***	-0.352***	-0.240*
	(0.112)	(0.133)	(0.136)
Observations	432450	594482	193757
R^2	0.036	0.064	0.093
Panel B.	Ln(Credit) if Accepted, 0 Otherwise		
Overconfidence MATH	-4.361***	-4.356**	-3.162*
	(1.374)	(1.669)	(1.699)
Geographic Controls	Y	Y	Y
South-Year FE	Y	Y	Y
Bank-Year FE	Y	Y	Y
Industry-Year FE	Y	Y	Y
𝟙(Credit Score)-Year FE	Y	Y	Y
Observations	432450	594482	193757
R^2	0.040	0.062	0.091

Table A.7: **Overconfidence, Collateral and Credit Supply: Robustness to Other Lending Factors**

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

	(1)	(2)	(3)	(4)	(5)
	$\mathbb{1}$(Loan Application Accepted)				
Overconfidence MATH × Collateral	0.357***	0.313***	0.366***	0.420***	0.304**
	(0.097)	(0.091)	(0.093)	(0.085)	(0.116)
Overconfidence MATH × QuantitativeMethods	-0.101				
	(0.070)				
Overconfidence MATH × BalanceSheet		-0.163***			
		(0.043)			
Overconfidence MATH × CreditRegister			-0.047		
			(0.042)		
Overconfidence MATH × QualitativeInfo				0.163***	
				(0.040)	
Overconfidence 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)
Overconfidence 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.8: **Overconfidence, Collateral and Credit Supply: Ln(Credit)**

The dependent variable is equal to the log of credit if the application is accepted, 0 otherwise. Overconfidence 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				
Overconfidence MATH×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×Collateral				-0.008	
				(0.011)	
Overconfidence MATH×Capital			0.562	0.558	0.615
			(0.569)	(0.565)	(0.574)
Overconfidence MATH×NPL/Assets			0.528	0.526	0.530
			(0.380)	(0.380)	(0.379)
Overconfidence MATH×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.9: **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. Overconfidence MATH is the province-level share of pupils who say that they find Mathematics easier than their classmates (INVALSI test). 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). Credit Score is Cerved Altman Z-score index, ranging from 1 (low risk) to 9 (high risk). 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 Accepted)			
Overconfidence MATH	-0.301**	-0.430***	-0.440***	-0.472***
	(0.151)	(0.128)	(0.130)	(0.125)
Overconfidence MATH× Tang/TotalAssets	0.857***	0.884***	0.798***	0.819***
	(0.278)	(0.288)	(0.277)	(0.277)
Observations	848131	848131	848131	848131
R^2	0.043	0.044	0.050	0.056
Panel B:	=Ln(Credit) if Accepted, 0 Otherwise			
Overconfidence MATH	-4.516**	-5.862***	-5.621***	-6.049***
	(1.863)	(1.640)	(1.631)	(1.577)
Overconfidence MATH× Tang/TotalAssets	11.833***	12.127***	10.148***	10.496***
	(3.608)	(3.746)	(3.512)	(3.522)
Geographic Controls	N	Y	Y	Y
South-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.10: **Overconfidence, Collateral and Credit Supply: Robustness to Other Geographic Factors**

The dependent variable is a dummy equal to one if the application is accepted. Overconfidence 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)		
Overconfidence 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)
Overconfidence 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.11: **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. Overconfidence 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		
Overconfidence MATH	0.192**	0.218**	-0.076		
	(0.076)	(0.104)	(0.049)		
Overconfidence MATH × Collateral			0.035**	0.034**	0.010*
			(0.017)	(0.015)	(0.006)
Collateral			-0.024**	-0.024**	
			(0.012)	(0.011)	
South-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.12: **Do overconfident managers match with riskier firms?**

The sample is restricted to firm-year observations before a "mover" manager is hired. Movers are defined as senior managers (CEO, CFO and other top executives) who were born in a different province from where the firm headquarter is located. The dependent variable is the firm credit score in columns 1-2; sales growth volatility in the past three years in columns 3-4; net profits over assets in columns 5-6, measured in the year before the mover joins the firm. Overconfidence 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	
Overconfidence 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
South-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

B The Model

The model has three periods. At time $t = 0$ the firm, 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 firm 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 firm receives at time $t = 0$ a perfectly informative private signal on the project's type. Thus, a realistic firm 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. Following prior work in the literature (e.g Manove and Padilla, 1999; Landier and Thesmar, 2008), overconfident firms are assumed to (wrongly) interpret bad signals as being good, and as a result they always want to implement the Growth strategy. At time $t = 2$ payoffs are realized.

We assume that banks are competitive and compare credit outcomes in two polar cases, when banks are "sophisticated" – i.e., they observe that borrowers are overconfident –, and when banks are "naive" – they wrongly consider overconfident borrowers as being realistic. Moreover, we always 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 $A < I$,[32] which are seized in case of default. The value of collateral for the bank is $\chi A < A$.

Credit equilibrium with sophisticated banks. When banks are sophisticated, they anticipate that overconfident borrowers will always find optimal to implement the Growth

[32] It is unenforceable in courts to seize borrowers' collateral for an amount greater than the promised repayment.

strategy. Lenders have better private information on the borrowers' type than the borrowers themselves, as in Inderst and Mueller (2006), because they may have better proprietary models to predict default than the simple credit score we observe or can analyze soft information received from meeting the borrower. It follows that banks' zero-profit condition is:

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

When the project is good, banks will receive the promised repayment R_{Bank} while they will seize firms' assets when the project is bad (and the overconfident borrower implements the growth strategy).[33] 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 (Manove and Padilla, 1999).

Credit equilibrium with naive banks. When banks are naive, they anticipate firms to implement instead the Safe strategy when the signal is bad. In that case, banks' (perceived) zero-profit condition becomes: $\tilde{R}_{Bank} = I$; and ooverconfident borrowers' perceived ex-ante profits are equal to: $\Pi_{Overconfident} = R_{Gr} - I$. It follows that overconfident borrowers' projects

[33]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.

are financed, and naive banks bear the losses associated to their bad investment decisions.[34]

[34] Banks' losses ex-post are equal to $\alpha\,(I - \chi A) > 0$.