Education and Credit: A Matthew Effect

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Abstract

Using a unique corporate loans dataset for entrepreneurs with small and micro enterprises, this paper examines the effect of educational attainment in the bank's credit decisions and subsequent individual and firm outcomes. Our results highlight a "Matthew Effect", where the initial advantage is self-amplifying. We find that entrepreneurs who obtain university education are more likely to apply for credit, obtain a higher credit score, and are granted better terms of lending. Via this credit channel, such entrepreneurs have significantly better future firm outcomes compared to those without university education. Furthermore, we find a key role for investments in innovation, intangible assets, and lower within-firm pay inequality.

Keywords: *Education; Credit; Higher education; Loan application; Bank credit decisions; Firm performance; Pay Inequality*

JEL Classification: *G21; G32; I23, I24; I26*

1. Introduction

Are entrepreneurs with higher levels of educational attainment more likely to apply for business loans and, if so, do they have higher chances to be granted the loan? Following the bank's credit decision, are education outcomes mirrored in differences in managerial investment decisions that lead to future individual and firm rewards? These questions are crucial in identifying how education affects credit decisions and the performance of small firms.

Highly educated and more skilled labor amplifies innovation and exacerbates technological advancements. If education levels play a role in the decision to apply for credit and for banks' credit decision, this can trigger a sequence of events at the managerial and firm levels, ultimately affecting firm performance and firms' economic outcomes. This occurs via a standard credit channel mechanism: loan origination generates liquidity and increases investment, which in turn helps firms to become more innovative, more profitable, and larger. These effects are especially important for small firms who rely heavily on bank credit and do not usually have access to alternative sources of funding (Berg, 2018; Delis et al., 2021).

We use unique data on loan applications to a large (systemic) European bank with nationwide coverage. We identify entrepreneurs as majority owners of small and micro firms, following the relevant definition of the European Commission (total assets less than €10 million). We observe repeated loan applications by the same applicants and construct a panel dataset over 2002-2018. Our final dataset includes 137,321 loan applications by 24,712 unique applicants. For each loan application, we have full information on the applicants' education and credit score, as well as applicants' gender, income, wealth, family situation, age, etc.; firm characteristics (including the firm's financial characteristics and region); loan characteristics (e.g., loan amount, maturity, collateral, purpose); and the bank's loan decision (granted or rejected).

Our empirical analysis covers three stages. First, we study the effect of education on the probability to apply for credit and analyze the bank's decision whether to grant the loan and under what terms. At this stage, we also consider the effect of education in reapplying if the loan has been previously rejected. Our hypotheses in the first stage are that individuals with higher levels of education are more confident, have a better understanding of the application process, and negotiate the terms of lending more efficiently. Equivalently, the bank considers education in the formation of the credit score.

In the second stage, we examine how educational attainment affects via the credit channel future firm outcomes, i.e., the probability of default, returns, leverage, and entrepreneurs' future income and wealth. Observing the bank's credit score is important at this stage because this score forms a sharp discontinuity in the bank's credit decision (Lee and Lemieux, 2010; Delis et al., 2021). The key assumption for the validity of our regression discontinuity (RDD) design is that applicants cannot consistently and/or precisely manipulate their credit score because the bank is a value-maximizing entity. We show how this holds in our setting with several relevant tests.

In the third stage of our analysis, we examine the key mechanisms driving our results. Our main hypotheses are that higher educational attainment (university degree and above) accentuates technological differences creating skill premia. Investment decisions for such entrepreneurs are more oriented towards technological innovation (R&D, intangible assets, and patents). Subsequently, within-firm pay inequality is lower because the firm selects high-wage workers (i.e., rising segregation). Thus, we analyze the role of within-firm pay inequality and investments in intangible assets, patents, and R&D to show what is driving the effects of education on entrepreneurial outcomes via the credit channel.

The key implication from our first-stage results is that higher education, specifically tertiary qualifications, creates a "Matthew Effect" [1] working via the credit channel.[2] This term refers to a cumulative advantage, where higher education qualifications result in higher probability to apply for a loan (by approximately 3.4 percentage points), a higher credit score (3.1 percentage points), and a higher probability to reapply within one year if they are rejected (3 percentage points). Moreover, higher education graduates face a lower loan spread of 7.9 basis points. When we consider applicants with an MBA and/or a PhD degree, these results become even more vigorous, potentially explained by an increase in the negotiation power of these individuals and/or more sophisticated and innovative projects. At this stage, the results are from either OLS or instrumental variables (IV) methods. In the OLS regressions, identification arises from individuals who obtain higher education within our sample period ("switchers"). Our IV represents the average share of entrepreneurs with higher education to the total entrepreneurs by region, industry, and year, 15 years prior each loan application (similar to Huang and Kisgen, 2013; Delis et al., 2021).

In the second stage, we show that firms of applicants with higher education have lower probability of firm default within three years after a loan origination compared to non-higher education applicants. Subsequently, using our RDD framework and depending on higher education attainment, we find that a positive credit decision by the bank has differential effects on: (i) the future probability of firm default (lower for higher education entrepreneurs), (ii) firm leverage (higher for higher education entrepreneurs), (iii) future entrepreneurs' income and wealth (higher for higher education entrepreneurs), and (iv) future within-firm pay inequality (lower for higher education entrepreneurs). These findings show that the effects identified in

[1] The term "Matthew Effect" was coined by the Sociologist Robert K. Merton (1968) to refer to his theory of cumulative advantage in science. The phenomenon was named after a verse in the Gospel of Matthew (13:12) which states that "for whoever hath, to him shall be given, and he shall have more abundance: but whoever hath not, from him shall be taken away even that he hath. Mrázová and Neary (2019) also refer to the "Matthew Effect" when examining selection effects with heterogeneous firms.

[2] From now onwards we refer to two groups: higher education, i.e. those with higher educational qualifications (tertiary, MSc, MBA and PhD degree) and non-higher education, i.e. those without higher educational qualifications (secondary, post-secondary, and non-tertiary).

the first stage of our analysis (especially the differential probability of loan application and loan origination between higher education and non-higher education entrepreneurs) trigger real differential effects among the two groups via the credit channel.

In the third stage of our analysis, we pinpoint the key mechanisms driving the real effects of the loan origination decision (our second-stage results). Using our RDD framework, we find differential effects of a positive credit decision by the bank on the ratio of intangible assets to total assets, the ratio of R&D expenses to total expenses, and the probability of a new patent. All these are considerably higher for those with higher education. Last, we show that the effect of the positive credit decision by the bank on the future returns and wealth of entrepreneurs with higher education is almost fully explained by asset intangibility and investments in high-skilled labor (low within-firm inequality), whereas this is not the case for the future returns and wealth of non-higher education entrepreneurs. Therefore, the combination of increased investments in innovation and lower within-firm pay inequality for entrepreneurs with higher education, account for most of the positive impacts of credit origination on future firm performance and entrepreneurs' wealth. This finding is consistent with Acemoglu (1999) and Song et al. (2019), who suggest that firms with rising returns to skill hire higher-paid employees compared to firms with lower returns to skill, due to technological advancements.

Our paper proceeds as follows. Section 2 discusses the theoretical underpinnings of our study and provides testable hypotheses. Section 3 presents our dataset. Sections 4 to 6 discuss the identification, models, and results of each of the three stages of our analysis respectively. Section 7 concludes.

2. Hypothesis development

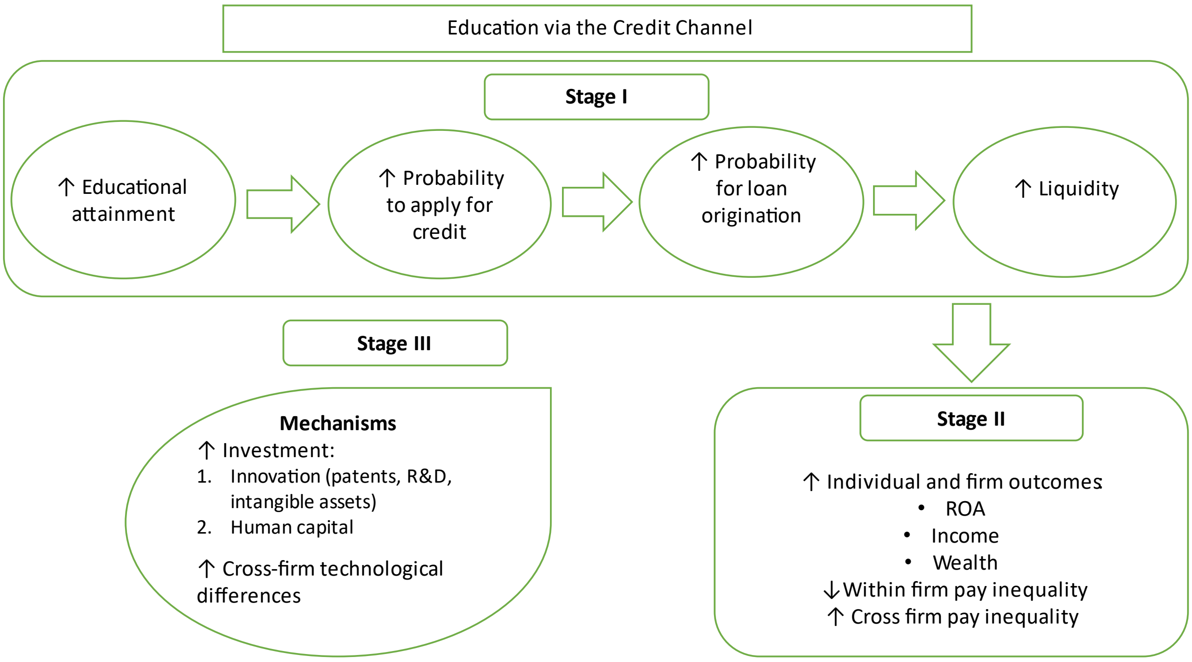
The credit channel operates as follows: loan origination generates liquidity, leading to more investment, increasing the profitability of the firm, and thus entrepreneurs' future wealth and income. Theoretically, different levels of educational attainment can affect the investment and managerial decisions, subsequently affecting future outcomes. To understand this process, we identify three key stages of analysis:

Stage I: Educational attainment affects entrepreneurs' decision to apply for a loan and bank's decision to grant a loan.

Stage II: Via its role through the credit channel under stage I, educational attainment affects future firm and individual outcomes.

Stage III: Mechanism: the effects identified under stage I and stage II are affected by how increased liquidity will be used for investment.

The chart below illustrates these three stages. In what follows, we discuss our main hypotheses regarding the relationship between educational attainment and future firm and individual outcomes via the credit channel.



2.1. *Education and probability of loan application*

We expect that entrepreneurs with higher education are more likely to apply for a loan. Over and above their innate ability, these individuals are more astute, understand the application process better (have higher financial literacy), and have higher levels of confidence. This hypothesis is in line with Zhao et al. (2005) and McGee et al. (2009), who suggest that education elevates entrepreneur's self-efficacy.

2.2. *Education and loan origination*

Higher education might act as a signal of ability for the bank, affecting the overall decision to grant credit. From the entrepreneur's side higher education might result in better negotiation power and abilities.

Probability of loan origination: We expect that the bank internalizes the level of applicant's educational attainment in the credit score. This reward enables higher education applicants to reach higher credit scores, increasing their chances of loan origination and credit access (Becker, 1964; Spence, 1973; Goodman et al., 2017).

Terms of lending: Due to higher levels of human capital development, higher education applicants have a better understanding of the loan origination process, greater self-efficacy, are more efficient at attracting capital and negotiate better loan terms, i.e., loan spread, amount, and collateral (Zhao, 2005; Yang and Yang, 2022).

2.3. *Education and investment*

We expect that entrepreneurs with differential levels of education undertake different managerial and investment decisions to exploit the increased liquidity after loan origination. These decisions may be affected by cross-firm technological differences, which in small firms are usually decided by the owners-entrepreneurs.

Investment in patents, R&D, and intangible assets: Our main hypothesis is that higher education accentuates technological differences creating a skill premium (Acemoglu, 1999). Consistent with the premise that smaller firms are often the most dynamic and innovative (e.g., Klapper et al., 2006), we expect that after a loan is granted the entrepreneurs with higher education direct investment more towards technological-oriented decisions, i.e. R&D, intangible assets, and patents.

Within firm-pay inequality: We also expect that higher education entrepreneurs receiving credit might invest in human capital. This can lead to a decrease in the within-firm pay inequality after loan origination, increasing segregation of high-wage employees to firms investing in higher innovation (Song et al., 2019).

2.4. Relation to the extant literature

To our knowledge our paper is the first that connects education with future firm and individual performance via the credit channel and differential managerial decisions. To this end, we build on three strands of literature. First, our paper adds to the banking literature that assesses the effects of the credit channel on firm performance. Delis et al. (2020) highlight how loan origination leads to better future firm performance and higher income inequality among small firms. Goodman et al. (2019) and Hartley (2019) connect individual's background (education and wealth) to future financial health, showing that education plays an important role on credit score formation. Papadimitri et al. (2020) find that higher education within a firm's board of directors impacts their credit rating positively. Marilanta and Nurmi (2018) and Lin et al. (2011) address the effects of educational attainment of entrepreneurs on their firm's performance.

Second, a substantial literature documents the interplay between technology and education on firm performance. Technological changes affect inequality due to labor demand shifts towards high skill groups creating skill premia (see Acemoglu and Autor 2011 for a review). Card et al. (2013) show that cross-firm wage inequality in Germany rises due to changes in workers' composition. High-wage workers are more likely to work in high-wage firms (increased '*sorting*'), and more likely to work with each other (rise in '*segregation*'). Song et al. (2019) observes that there is a rise in earnings inequality in the U.S. and attribute one-third of that rise to within-firm pay inequality and two-thirds to cross-firms pay inequality.

Finally, our paper relates to the management and psychology literature that connects education to increased self-efficacy and different managerial decisions. Zhao et al. (2005) and McGee et al. (2009) examine how increasing higher education levels impact the entrepreneurial self-efficacy index positively. Nisula and Olander (2021) note the importance of self-efficacy to entrepreneurial intentions. Ajayi and Ross (2020) highlight the key role of education on individual's financial development.

3. Data

There exists limited panel data on credit access and educational attainment to allow for a systematic examination of individuals over time. We empirically answer our research questions using a unique corporate loans dataset for entrepreneurs making applications to a major systemic European bank with nationwide coverage.

3.1. Dataset

The bank from which we obtain the data is a systemically important financial institution according to the definition of the European Banking Authority (EBA). We have access to its full loan portfolio, applications, originations, and rejections, for the period from 2002 to 2018.[3]

[3] A similar data set is used by Delis et al. (2020), please see for an extensive analysis on how this bank is representative of European banks in terms of size, operations, structure, etc. Furthermore, we run additional checks to establish that the bank and the firms in our sample have very similar characteristics when compared to other systemic European banks and other small European firms, respectively.

Similar to Delis et al. (2020), we focus on the use of data for the bank's loans to domestic small and micro-firms (total assets of up to €10,000,000 per the EU definition). The bank operates on a global scale and provides credit to all business types. Using data from a single bank is common practice when detailed data are required (e.g., Delis et al., 2020; Berg, 2018; Iyer and Puri, 2012; Adams et al., 2009).

Our sample is restricted to small and micro-enterprises because we require that loan applicants are majority owners (own more than 50%) of the firm. We consider all corporate loan types, including working capital loans, real estate loans, venture loans for start-ups, lines of credit, etc. For each loan application, we have detailed information on key characteristics of the applicant, firm and loans, including the bank's loan decision (approved or rejected). Importantly, we have access to the applicant's credit score on which the bank's decision is conditional on. We also know whether the applicant has an exclusive relationship with the bank.[4] The bank records which firms apply for loans to other regulated and supervised banks (by the European Banking Authority or the country's credit register). Our bank has access to information on the timing of the loan applications and their outcome. Using these data and repeated loan applications by the same applicants, we construct a panel data set of loan applicants over the period 2002–2018.

For most of the applicants, we observe more than one loan application during our sample period. In order to compare across individuals, it is necessary to observe firm and

[4] Applicants who have an exclusive relationship with this bank are credit constrained (even from other conventional banks) if our bank rejects their application. For small firms, having an exclusive relationship with a bank is common and our full sample suggests this is the case for 65% of the firms. Using summary statistics from previous studies on multiple or exclusive lending relationships, we note that Berger et al. (2011) document a 71% exclusive relationship between banks and SMEs in three European countries (Germany, Italy, and the UK), while this is less often the case in the U.S. (Berger et al., 2014, document a 57% rate). It is hard to find much more evidence precisely on whether (small) firms have one or more banking relationships in north European countries. Farinha and Santos (2002) report similar statistics for Portugal (70% of firms with less than 10 employees have one bank relationship). More recently, Bonfim at al. (2018) report a mean value of 2 banks for small Portuguese firms, but the Portuguese banking sector is much less concentrated than the one in our bank's country. Essentially, the available evidence suggests that the percentage of exclusive relationships in our sample is comparable to previous papers on relationship banking.

applicant characteristics at two or more points in time. Thus, we maintain a firm-year balanced panel data set. We discard loans from applicants who never reapply for loans. Essentially, all individuals reapply for loans within a four-year period. In other words, all observed firms have a relationship with the bank from 2004 onward (the bank has information for the applicants from 2002 onward).[5]

This approach results in a total of 414,730 observations. The panel has more observations than the number of loans because firm owners do not apply for a loan every year. However, the bank continues to hold information on the applicant characteristics after the loan application because when a new application takes place in the future, the bank requests information for applicants' income and wealth retrospectively. Using this information, we generate a panel dataset of 138,633 loan applications by 24,712 unique applicants during the period from 2002 to 2018. From these loan applications the 84.2% were originated (116,753 loans).[6]

In relation to applicant characteristics, we observe age, gender, education, income, wealth, marital status, and the number of dependents. Furthermore, we have a large range of firm characteristics such as size, leverage, return on assets (ROA), liquidity, and the firm's region and industry. At the loan level, we observe the loan characteristics where the loan is originated, i.e., spread, amount, maturity, and collateral.

We define all the variables used in our analysis in Table 1 are report summary statistics in Table 2. For illustration purposes, the mean applicant is close to having tertiary education, is approximately 45 years old, married, and has one or two dependents.

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[5] This comes at the expense of introducing sample selection. We show that running our analysis on an unbalanced sample or using estimations techniques to deal with selection does not affect our inferences and in fact strengthens the results in the cases where these are statistically significant. However, using an unbalanced panel implies that we do not have important dynamic information on certain applicant characteristics (especially income, wealth, and changes in family status) and an observed exclusive bank-firm relationship. Results from an unbalanced panel are available on request.

[6] This figure is slightly lower than the equivalent reported in the Survey of Access to Finance of Enterprises (SAFE). However, SAFE includes a sample of relatively safer medium-sized firms.

[Please insert Tables 1 & 2 about here]

3.2. Key variables

We group entrepreneurs into six levels of *Education*: (i) no secondary; (ii) secondary; (iii) post-secondary/non-tertiary; (iv) tertiary (university); (v) Master of Science degree (MSc); (vi) Master of Business Administration degree (MBA) or Doctor of Philosophy (PhD). A key aspect is that 2,711 individuals ('*switchers*') change from non-tertiary (university) education to tertiary education, creating a time-series element that is important for empirical identification.[7]

Table 3 reports summary statistics separately by *Education* levels and provides a first indication of a "Matthew effect", i.e. a significant increase in the probability to apply and obtain a loan, the credit score, and firm outcomes as *Education* increases. Also, we observe that entrepreneurs with higher education (university degree and above) face better terms of loan (i.e., amount, spread, maturity, and provisions) and their firms have a lower probability to default.

[Please insert Table 3 about here]

Figure 1 shows the coefficient estimates and confidence intervals in the probability of loan application by education level. The point estimates are for those with: (i) secondary or below; (ii) post-secondary/non-tertiary; (iii) tertiary and MSc; and (vi) MBA or PhD. We observe a positive relationship between the probability of loan application and educational attainment. We observe the most significant increase when comparing higher education to non-higher education applicants.

[Please insert Figure 1 about here]

[7] When we do not know the precise year of the change (i.e., there is no loan application in two consecutive years), we assume that this change happens in the middle of the time interval between the two loan applications. We make the same assumption for marital status. We also complete the observations with the last credit score calculated by the bank. Thus, if there is a loan application in year t but not one in year t+1, we impute in year t+1 the credit score in year t. Different timing assumptions do not affect our main results.

Credit score is a statistical tool constructed by financial institutions to determine the credit health of an individual or a firm. In our panel, *Credit score* ranks the entrepreneurs' credit riskiness and is used by the bank to decide whether to extend or deny credit as well as the lending terms. If a credit score is awarded above a specific cutoff point, the bank originates the loan; for a credit score below this cutoff, the bank denies the loan (or suggests re-examination later). We are not permitted to disclose the precise cutoff, therefore we normalize it to zero.

The *credit score* contains a mix of hard and soft information. Hard information refers to all information systematically recorded on paper (on the application files). Soft information refers to the residual: what explains the credit score that is not included explicitly on paper. For example, soft information contains the perception of the applicant/firm, investment idea, and the strength of the bank-firm relationship.

3.3. Control variables

The control variables represent the characteristics of the entrepreneur and the firm. It is possible that variations in the outcome variables are due to differences in other individual characteristics such as *Gender, Age, Income, Wealth, Marital status*, or number of *Dependents.* For example, previous research has identified that males are more likely to apply for credit than females. Also, entrepreneurs who are younger (on average), married, and with a lower number of dependents are also more likely to apply and obtain loans. Further, higher *Wealth* and *Income* are positively correlated with access to education and credit (Morgan and David, 1963; Delis et al., 2020). Finally, we include firm characteristics such as *Size, Leverage, Return on Assets* (*ROA*), *Liquidity*, and firm region and industry (Jimenez et al., 2014).

In the third stage of our empirical analysis, we include additional variables to pinpoint the key mechanisms of our main findings. We estimate future within-firm *Pay inequality* as the annual salary of the owner divided by the mean salary of employees (excluding the owner). Investment in *Intangible assets* is measured by the ratio of intangible assets to total assets. *R&D expenses* is measured by the ratio of R&D expenses to total expenses. We also use a dummy variable to indicate the probability of a new patent (*Patents*).

4. Stage I: Loan application and origination

4.1. Empirical model and identification

In stage I, we study the effect of education on the probability of loan-application and re-application after rejection. Also, we examine how education affects loan origination and terms of lending (i.e., amount, collateral, and spread). In a preliminary analysis and consistent with Figure 1, we find that what matters most is higher education. We thus estimate the following models:

$$Apply_{it} = a_0 + a_1 Higher\ education_i + a_2 x_{i(f)t} + u_{it}, \tag{1}$$

$$Granted_{it}(Credit\ score_{it}) = a_0 + a_1 Higher\ education_{it} + a_2 x'_{i(f)t} + u_{it}. \tag{2}$$

Apply is a binary variable, taking the value 1 if an individual *i* in our sample applies for a loan at year *t* (and 0 otherwise). *Granted* is a binary variable equal to 1 if the loan is originated by the bank (i.e., the credit score is positive) and 0 if the loan application is rejected (i.e., the credit score is negative). *Credit score* is a continuous variable normalized around 0, that is the value above (below) which the loan is granted (rejected). *Higher education* is a dummy variable that takes the value 1 if the individual (*i*) has completed higher education and 0 otherwise. In alternative specifications, we use *Professional education*, which takes the value 1 if the individual (*i*) has completed professional education (MBA/PhD). The vector *x* represents control variables reflecting individual (*i*) or firm (*f*) characteristics. All specifications include individual and year fixed effects.

We estimate linear probability models via OLS and 2SLS, which fare better compared to nonlinear models in the presence of several fixed effects. For equation 1, we use the full sample of 414,730 individual-year observations. For equation 2, when *Granted* is our dependent variable, we use the sample of 137,321 granted loan applications because this sample can include only cases where *Apply* equals 1. We revert to the full sample when *Credit score* is our dependent variable.

Our identification strategy considers two approaches: observing switchers, i.e., the individuals who obtain higher education during our sample period and thus see a change in *Higher education* from 0 to 1, and using an IV approach. We capture a significant part of the time-varying applicant adverse selection (that is unobserved to the bank) using the switchers, for which we have 2,711 cases. We do this by including individual (equivalent to firm) fixed effects. We perceive the individual fixed effects as a measure of innate ability. Then, our estimates on *Higher education* essentially compare the outcome variables for the same individuals/firms before and after obtaining a university degree. Equally important, the fact that different individuals obtain higher education on different years renders the probability of significant correlation of *Higher education* with other unobserved to the bank individual characteristics very small (and thus any role for omitted variable bias quite limited). To ensure that the sample of switchers is representative, we compare our results with an OLS model without fixed effects and find consistently similar estimates throughout our specifications.

Even though it is unlikely that a residual individual characteristic affects both the *change* in education and the banks' loan decision *on the same year* (even if this exists, the bank would probably not know and thus the loan decision would not be affected) we also estimate a 2SLS model. We use the variable *Regional education* as our IV. Following Huang and Kisgen (2013) and Delis et al. (2021), we construct our IV to represent the average share of entrepreneurs with university (or professional) to the total entrepreneurs by region, industry, and year, 15 years prior each loan application. For example, the value for the share of 1990 is the instrument for the loans originated in 2005.

Historical regional instruments have been used extensively in the literature (Duranton and Turner, 2012; Huang and Kisgen, 2013; Delis et al., 2021). The exclusion restriction backing such instruments, is that historical regional characteristics are very unlikely to directly influence contemporary economic outcomes. In our case, the premise is that the higher the regional share of educated entrepreneurs 15 years prior to loan application, the more likely a firm located in that region is to have a highly educated entrepreneur now. While this variable is plausibly correlated with the educational status of the entrepreneur, it is predetermined and unlikely to affect our outcome variables but only through its effect on *Higher education* (especially given the use of contemporary controls for these variables).

4.2. Estimation results

We report estimation results from equation 1 in Table 4. In all specifications, we control for individual and firm characteristics, and use the fixed effects noted in the lower part of the table. We cluster the standard errors by individual applicants.[8] In the first column, the OLS results show that obtaining higher education (when previously an individual did not given the individual fixed effects) has a statistically and economically significant effect on the probability to apply for a loan (1.8 percentage points). This becomes 2.4 percentage points for professional education (MBA/PhD), as reported in column 3.[9]

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[8] In alternative specifications we also cluster on the regional level. This might be important especially for the IV regressions for which the instrument is observed at the regional level. The country where our bank is based is divided to a substantial number of regions which allows the use of such a regional instrument. Results are reported in Table A2 of the appendix. Clustering at a more aggregate level (by region) does not affect our inferences.

[9] For all our results we have run an alternative specification to examine whether the effect is more potent when we combine education with gender. The results are available upon request. We persistently find no significant effect from the interaction of education with gender.

The equivalent 2SLS results are in columns 2 and 4 of Table 4. The first stage results fulfil the relevance condition, indicating a strong correlation between regional education and *Higher education* (column 2) or *MBA/PhD education* (column 4). Specifically, a one-standard-deviation higher *Regional education* is associated with a 21.2 percentage points higher probability that the loan applicant has higher education (statistically significant at the 1 percent level). This is intuitive, given that the pre-existence (15 years prior to loan application) of more educated entrepreneurs in a given region, industry, and year, yields a higher probability that the loan applicant has higher education at year *t*. The second stage results in column 2 show that obtaining higher education yields a 3.4 percentage points higher probability for loan application. Again, we find stronger estimates when considering the effect of MBA/PhD education (column 4).

[Please insert Table 4 about here]

To ensure that the use of individual fixed effects appropriately captures the characteristics of our whole sample, in a robustness exercise we exclude them from our analysis presented in Table A1 of the appendix. The results remain statistically significant and more potent, i.e., 2.3 percentage points higher probability to apply for those with higher education and 4.3 percentage points for those with professional education.

Next, we estimate equation 2 using the 137,321 observations for which the bank makes a credit decision. Also, given that the *Credit score* perfectly defines the bank's decision to grant the loan, in an alternative specification, we revert to the full sample, considering the full information of those who were not granted a loan. To do so, we use *Credit score* as our dependent variable.

[Please insert Table 5 about here]

Table 5 reports the results, showing a statistically significant effect of *Higher education* on both *Granted* (first two columns) and the *Credit score* (last two columns). According to the

2SLS results in column 2, individuals that obtain higher education are 1 percentage point more likely to be granted a loan. The equivalent results in column 4 show that applicants obtaining higher education have a higher credit score by 3.1 percentage points. These results effectively show how much the bank values higher education in its credit score system.

[Please insert Table 6 about here]

Along the same line, the results in Table 6 show that individuals obtaining an MBA/PhD degree have a 1.6 percentage point higher probability to be granted the loan (results in column 2). When we use the *Credit score* as our dependent variable, the results in column 4 suggest that individuals obtaining an MBA/PhD have a higher credit score by 5.6 percentage points compared to the non-professional base case. This suggests that professional education leads to even higher credit scores.

In the next step, we examine how differences in *Education* affect the probability that rejected applicants reapply for a loan within a specific period (one or two years). We expect that rejected applicants obtaining higher education or professional qualifications may seek to reapply for a loan sooner. To this end, we re-estimate equation 1 with the dummy dependent variable *Reapply*, which takes the value 1 for the rejected applicants that reapply for a loan within one or two years after the bank's credit decision (value equal to 0 for those that did not reapply).[10] For this exercise, we use the sample of rejected applicants (21,284 observations).

Columns 1 and 2 of Table 7 report OLS estimations for a model where the base case are individuals with no higher education and no MBA/PhD degree respectively, whereas columns 3 and 4 report the equivalent 2SLS estimations.[11] We use a one-year window in columns 1 and 3, and a two-year window in columns 2 and 4. The results show a higher

[10] We also know that those applicants did not reapply for credit to another bank (at least at banks being actively regulated and supervised by national or European authorities).
[11] An alternative would be to estimate duration models (e.g., Cox hazard models). We do not favor this approach here because, by construction of our panel to observe important applicant characteristics, individuals reapply for loans within four years. Thus, we document educational attainment differences in the readiness to apply for credit within the first two years post-rejection.

probability of applicants with higher education to reapply within one or two years after their rejected application. Specifically, based on the 2SLS estimates, we find that rejected applicants with higher education are 2.5% (3%) more likely to apply for a loan in the one-year (two-year) window after the original rejection. Interestingly, these probabilities do not increase for the case of rejected applicants with an MBA/PhD degree. In particular, rejected applicants with professional education have a 2% (2.4 %) higher probability to reapply within one-year (two-year) window after rejection, which may indicate that such applicants take more time to consider and develop their proposals for the new applications after rejection.

[Please insert Table 7 about here]

A last exercise under the loan application/origination analysis considers the effects of *Education* on loan characteristics. To this end, we estimate equation 2 using *Loan amount*, *Loan spread*, and *Collateral* as the dependent variables. Panel A shows that higher education significantly lowers the loan spread but does not affect the loan amount or the probability that the loan has collateral. The results for *Loan spread* (based on column 4) suggest that individuals obtaining higher education face 8 basis points lower spread compared to those without higher education. This result can potentially be explained both from the entrepreneur's side (demand effect), suggesting that individuals with higher education can better negotiate the lending terms, and from the bank's side (supply effect) with banks directly considering individuals with higher education a less risky investment.

[Please insert Table 8 about here]

Interestingly, considering individuals with an MBA/PhD in Panel B, we find that apart from a statistically significant effect on the loan spread, those individuals are granted a 2.7% larger loan amount (statistically significant at the 10% level). This result can be explained by an increase in the negotiation power of these individuals and/or from the nature of their projects which might be more expensive and technologically sophisticated.

5. Stage II: Future firm and individual outcomes

5.1. Empirical models and identification

Noting that higher education graduates are more likely to apply for a loan and that the bank is more likely to grant them one, our next question is whether *Education* affects firm outcomes via the credit channel. Specifically, we consider the effect of education on future outcomes, such as the probability of firm default (*Default*), firm profitability (*ROA*) and leverage, within-firm pay inequality, and individual outcomes such as income and wealth. Although the individual fixed effects ('*switchers*') allow us to control for innate ability, the IV might not be suitable for future firm performance because this is a function of several current and future developments that might be correlated with regional dynamics.

A solution to this identification problem comes from the dichotomy between the bank granting the loan or not (*Granted* =1 versus *Granted* =0). This dichotomy creates a sharp RDD (e.g., Berg, 2018; Delis et al. 2021). The credit score is the strict tool the bank uses to reach its credit decision: for credit scores above (below) a cutoff point (here normalized to 0), the bank always grants (rejects) the loan. The theoretical channel behind this design is that loan origination generates liquidity and increases firm's investment, which in turn increase profitability and decrease the future firm probability of default. The key assumption for the validity of this RDD design is that applicants cannot consistently and precisely manipulate their credit score because the bank is a value-maximizing entity aiming to minimize non-performing loans.

To this end, we estimate the following model:

$$Forward\ outcome_{i,t+3} = a_0 + a_1 Granted_{it} + a_2 x'_{i(f)t} + u_{it}. \qquad (3)$$

Forward outcome is either *Default*, *Forward ROA*, *Forward leverage*, *Future pay inequality*, and individual's *Future income* and *Wealth*, all observed three years after the bank's credit decision (i.e., at t+3). The credit score is the assignment (also referred to as "the running" or "the forcing") variable (Imbens and Lemieux, 2008; Lee and Lemieux, 2010).

Equation 3 examines the heterogeneous effect of granting a loan between higher education and non-higher education applicants. Using an RDD with interaction terms to infer heterogeneous effects is not common practice in the related literature, thus we identify the effect of *Education* by estimating equation 4 twice for each of the two groups. We use a nonparametric local linear regression, which has the advantage of assigning higher weights to observations closer to the cutoff value of 0.[12] We determine the optimal bandwidth using the approach in Calonico et al. (2014), and for efficient estimation we base our inference on the local-quadratic bias-correction in Calonico et al. (2018) and Cattaneo et al. (2018).

5.2. RDD validation and estimation results

In Figure 2, we provide a graphical representation of the relation between the *Credit score* and *Forward ROA* for the full sample of loan applicants (i.e., *Apply* = 1), as well as for the separate samples of applicants with and without higher education. The points represent local sample means of the applicant's ROA for a set of disjointed bins of control and treatment units spanning the full sample. We select evenly spaced bins that mimic the underlying variability of the data using spacings estimators.[13] The continuous line represents a fourth order polynomial fit used to approximate the conditional mean of applicants' income below and above the cutoff. All the figures show clear upward shifts in *Forward ROA*. This indeed suggests that the treatment (*Granted* = 1) entails a sharp discontinuity in both the outcome

[12] In general, the advantage of using two separate regressions is that the slopes of all the right-hand side variables are allowed to differ, and this is preferable when these variables have largely different correlations by education. In our context, the two separate regressions have another important advantage. The "rdrobust" Stata tools by Calonico et al. (2014), Cattaneo et al. (2016), Calonico et al. (2018), Cattaneo et al. (2018), and related papers allow identifying the validity of the RDD and produce robust estimates. These imply improved inference and associated transparency. However, these tools come at the expense of some flexibility loss, especially as we cannot introduce interaction terms. In the technically most relevant recent study, Berg (2018) uses a local linear regression and more standard software allowing the regression function to differ on both sides of the cutoff point (see also Lee and Lemieux, 2010, p. 318). Using such an approach does not affect our main inferences.
[13] Essentially, these represent the "interesting" bins as selected by the software and not the full set of observations.

variables for the full sample and for the separate samples. In that sense, the local linear regression helps with identification, as the family of nonparametric models is better suited to account for non-linearity.

[Please insert Figure 2 about here]

In Figure 3, we run a manipulation test proposed by Cattaneo et al. (2018). The test uses the local quadratic estimator with cubic bias-correction and a triangular kernel. Consistent with the validity of a sharp RDD, the formal test shows no statistical evidence of manipulation of the assignment variable. This is theoretically plausible because it is highly unlikely that loan applicants systematically manipulate their credit scores.[14] Moreover, all our control variables do not jump at the cutoff (a full set of figures is available on request).

[Please insert Figure 3 about here]

Following the validity tests, we report our baseline RDD results in Table 9. We report the bias-corrected RDD estimates with a conventional variance estimator. The equivalent results with a robust variance estimator are almost the same. For the estimation, the RDD method uses a specific number of observations right and left of the cutoff (reported as effective observations in Table 9); this also implies that the approach is less sensitive to difference in the sample size between those with and without higher education. Columns 1 to 3 report the effects, three years after the bank's decision to grant the loans, on firm's probability of *Default*, *Future ROA*, and *Future leverage* for individuals with a higher education, whereas columns 4 to 6 present the equivalent for individuals without higher education.

The estimate in column 1 suggests that a positive credit decision lowers the probability of *Default* for applicants with higher education by a substantial 16.4 percentage points. The equivalent estimate for applicants without higher education (column 4) is an even higher 24.5

[14] Moreover, in the bank's country there is no evidence of fraud in loan applications, not even in the years prior to the global financial crisis.

percentage points. This 8-percentage points difference is highly statistically significant (at the 1% level) and suggests that applicants without higher education rely much more on loan origination to avert their firm from defaulting. This finding is fully consistent with our stage I analysis, whereby entrepreneurs with higher education are more likely to apply for a loan (or reapply after being rejected) and being granted one.

The corresponding effects on *Forward ROA* and *Forward leverage* are even more indicative. We find that a positive credit decision increases *Forward ROA* for applicants with higher education by 0.06 more than the corresponding increase of applicants without higher education. This is a large difference given the mean average ROA is 0.068 in our sample. Interestingly, the effect of a positive credit decision on *Forward leverage* highlights a different pattern between the two groups. Entrepreneurs with higher education are more willing to increase their firm's *Future leverage*, with the effect being statistically and economically significant; leverage increases by 1.3 percentage points and it is statistically significant (at the 5% level). In contrast, the effect is statistically insignificant for those without higher education.

[Please insert Table 9 about here]

Apart from the effects of education on standard firm outcomes, we observe that higher levels of education, through the credit channel, also affect the relative wages of the firm's owner compared to the rest of the employees (within-firm pay inequality). We have two ways to capture this wage inequality. First, we observe whether individual's *Future income* and *wealth* is affected by education through the credit channel. Second, we examine how different levels of education affect the future within-firm *Pay inequality*. Results are in Table 10. Once again, we estimate equation 4 for applicants with and without higher education. The dependent variable for columns 1 and 3 is the individual's *Future income*; for columns 2 and 4 is the individual's *Future wealth*; and for columns 3 and 6 is *Future pay inequality*.

[Please insert Table 10 about here]

We find that a positive credit decision from the bank leads to a 3.8 percentage points increase in the income of entrepreneurs with higher education, whereas the equivalent effect for the applicants without higher education is 2.1 percentage points. Similar differences are observed for results regarding the individual's *Future wealth* showing a difference of 1.4 percentage points, higher for those with higher education. These results are consistent with our premise that less education, via the credit channel, exacerbates income and wealth inequality, contributing to a Matthew effect. Interestingly, from columns 3 and 6 we observe that entrepreneurs with higher education are more likely to reward their employees with salaries more equal to their own. We find that loan origination has no significant effect on the within-firm pay inequality for the case of higher education entrepreneurs, whereas the effects are statistically and economically significant for the entrepreneurs without higher education. For the latter, we find that future pay inequality increases after the loan origination by 4 percentage points.

6. Stage III: Identifying the mechanisms

6.1. Empirical models and identification

In this final stage, we examine the mechanisms driving our results. According to our theoretical hypotheses in section 2, we expect that entrepreneurs with higher education undertake different managerial and investment decisions. First, they may invest in innovation capabilities, such as R&D, patents, and intangible assets. In these technological frontier firms, such investments may result to higher future firm performance and individual outcomes after loan origination. Second, consistent with the results in the previous section, entrepreneurs with higher education may hire employees with similar *Education*, creating skill premia observed in their employees' wages, reducing within-firm pay inequality.

To pinpoint the above mechanisms, first we re-estimate equation 4 with *asset intangibility*, *R&D* expenses, and *patents* as dependent variables. Again, we use our RDD framework. Second, using a similar setup, we estimate *Future ROA* and *Future wealth* equations while controlling for asset intangibility and within-firm-pay inequality to infer their impact on the estimate on *Granted*.

6.2. Results

Table 11 reports that firms owned by entrepreneurs without higher education indeed have higher within-firm pay inequality after loan origination, whereas the effect is insignificant for firms owned by entrepreneurs with higher education. This is a first indication consistent with our hypothesis that higher education entrepreneurs hire employees with similar wages to themselves. To further explain this finding, we examine whether higher education entrepreneurs use credit to invest more in R&D, patents, and intangible assets, which in turn increases their firms' profitability and their own future income and wealth.

In panel A, column 1, we first show that entrepreneurs with higher education who had their loans originated, invest, on average, 11 percentage points more in intangible assets than applicants with higher education who were not granted the loan. The equivalent effect for the non-higher education entrepreneurs (column 4) is statistically insignificant. Also, when we take the difference of the coefficients between columns 1 and 4, we find that higher education entrepreneurs invest, on average, 11 percentage points more in intangible assets (the coefficient for non-higher education entrepreneurs in column 4 is statistically insignificant).

Similarly, the results in Panel A, column 2 show that applicants with higher education who have their loans originated are 8 percentage points more likely to use patents than applicants with higher education who were not granted the loan. There is no significant effect on asset intangibility or patent use for applicants without higher education, indicating that they do not direct more credit towards innovation after a loan origination. The effect of loan origination on *R&D expenses* is positive for both higher education and non-higher education entrepreneurs, but again the effect is stronger for the higher education group (10 percentage points vs. 6 percentage points, respectively).

[Please insert Table 11 about here]

Next, we examine the effect of *Granted* on firm and individual outcomes (Table 11, Panel B) by directly controlling within the RDD for *Asset intangibilit*y and *Within-firm pay inequality* (separately and combined) to examine their impact on the coefficient on *Granted*. We find that sequentially adding these controls significantly lowers the impact of *Granted* on *Future ROA* and *Future wealth* for the higher education entrepreneurs (left-hand side specifications of Panel B). Adding them both (specifications 13 and 14) accounts for almost all the statistically significant impact of *Granted*, with the relevant coefficient falling from 0.067 (0.031) in the *Future ROA* (*Future wealth*) specification without these controls to 0.035 (0.021) in the specification with both controls. The estimates in specifications 13 and 14 are barely statistically significant at the 10% level or insignificant, while the original estimates without the controls in specifications 1 and 2 are statistically significant at the 1% level.

Evidently, this is not the case for those without higher education (as shown on the right-hand side specifications of Panel B). In these specifications adding *Asset intangibilit*y and *Within-firm pay inequality* in the baseline specifications does not lower the coefficient on Granted as much. Comparing the results in columns 15 and 16 to those in columns 3 and 4, we find only small reductions in the economic and statistical significance of the coefficients on *Granted*. In a nutshell, a key driver of the significantly higher firm *Future ROA* and individual *Future wealth* for entrepreneurs with higher education, are investments in intangible assets and lower within-firm pay inequality financed through loan origination. These findings highlight how differences in entrepreneurs' educational attainment generates higher income and wealth differences for these entrepreneurs via the credit channel, whereby a key role is played by investment in intangible assets and high-quality employees.

7. Conclusions

This paper investigates the effect of differential education on entrepreneurial and bank credit decisions, and subsequent individual and firm outcomes, via the credit channel. Our analysis uses a unique sample of corporate bank loans by majority owners of small and micro enterprises from a major European bank.

We find that entrepreneurs who obtain higher qualifications are more likely to apply for credit, obtain a higher credit score, and are more likely to be granted better terms of lending. Subsequently, higher (tertiary) educated entrepreneurs, due to higher chances of loan origination, have significantly enhanced future firm outcomes (firm profitability, probability of default, leverage). This higher firm performance leads to higher future individual income and wealth. Our combined results highlight a Matthew effect, where the initial advantage of obtaining higher levels of education magnifies over time and is rewarded via the credit channel to produce greater firm and individual outcomes.

We identify that the key mechanisms driving our findings are the differential managerial and investment decisions by highly educated entrepreneurs, which accentuate cross-firm technological differences and within-firm pay inequalities. Investment decisions for highly educated entrepreneurs are increasingly oriented towards technological innovation (R&D, intangible assets, and patents). Equivalently, their managerial decisions focus on investments in human capital and selecting higher-waged workers, i.e. rising segregation.

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Table 1. Data and variable definitions

Variable	Description
A. Dimension of the data	
Individuals	Loan applicants who have an exclusive relationship with the bank and are majority owners (own more than 50%) of a firm. These borrowers apply to the bank for one or more business loans during the period 2002-2018 and the loan is either originated (fully or at least 75% of the requested loan amounted) or rejected (bank advice against proceeding with the application, fully rejected or originated only up to 25% of the requested loan amount). Due to the exclusive relationship, the bank holds information on the applicants even outside the year of loan application.
Year	Our sample covers the period 2002-2019. Applications end in 2018 and we use one more year of firm financial ratios (2019) to examine future firm outcomes.
B. Variables	
Apply	A dummy variable equal to 1 if the individual applied for a loan in a given year and 0 otherwise.
Education	We have information on the level of education, which corresponds to an ordinal variable ranging between 0 and 5 if the individual completed the following education. 0: No secondary; 1: Secondary; 2: Post-secondary, non-tertiary; 3: Tertiary; 4: MSc; 5: MBA or PhD.
Higher education (HE)	A dummy variable equal to 1 if the individual completed tertiary education or higher (i.e., Education > 2) and 0 otherwise (i.e., Education < 3).
Professional education	A dummy variable equal to 1 if the individual completed MSc/MBA/PhD education (i.e., Education > 3) and 0 otherwise (i.e., Education < 4).
Income	The euro amount of individuals' total annual income (in log) in the year of the loan application and the two years before the application. For the missing years, we input the predicted value of the regression of the last available observation of income on the mean income by region, year, and industry.
Wealth	The euro amount of individuals' total wealth other than the assets of the firm and minus total debt (in log). The bank observes this in the year of the loan application and the two years before the application. For the missing years, we input the predicted value of the regression of the last available observation of wealth on the mean wealth by region, year, and industry.
Gender	A dummy variable equal to 1 if the applicant is a male and 0 otherwise.
Age	The applicant's age.
Marital status	A dummy variable equal to 1 if the applicant is married and 0 otherwise.
Dependents	The number of dependents.
Firm size	Total firm's assets (in log).
Firm leverage	The ratio of firm's total debt to total assets.
Firm ROA	The ratio of firm's after tax profits to total assets.
Firm cash	The ratio of cash holdings to total assets.
Forward ROA	The mean *Firm ROA* in the three years after the year of the loan application.
Forward growth	The mean increase in *Firm size* in the three years after the year of the loan application.
Forward leverage	The mean *Firm leverage* in the three years after the year of the loan application.
Credit score	The credit score of the applicant, as calculated by the bank. There is a 0 cutoff: positive values indicate that the loan is granted and negative values indicate that the loan is denied.
Applications	The number of applications to the same bank before the current loan application.
Granted	A dummy variable equal to 1 if the loan is originated (Credit score>0) and 0 otherwise (Credit score<0).

Default	A dummy variable equal to 1 if the firm defaults up to three years after the loan origination and 0 otherwise.
Loan amount	Log of the loan facility amount in thousands of euros.
Loan spread	The difference between the loan rate and the LIBOR (in basis points).
Maturity	Loan maturity in months.
Loan provisions	A dummy variable equal to 1 if the loan has performance pricing provisions and 0 otherwise.
Collateral	A dummy variable equal to 1 if the loan has collateral guarantees and 0 otherwise.
Regional education	The share of entrepreneurs with university (or professional) education to total entrepreneurs by region, industry, and year, 15 years before the loan application.

Table 2. Summary statistics

The table reports the number of observations, mean, standard deviation, minimum, and maximum for the variables use in the empirical analysis. The variables are defined in Table 1, except from *Application probability*, which is obtained from the estimation of equation (1).

	Obs.	Mean	St. dev.	Min.	Max.
Panel A: Full sample					
Apply	414,730	0.331	0.471	0	1
Education	414,730	2.997	1.015	0	5
Higher education	414,730	0.503	0.473	0	1
Professional education	414,730	0.188	0.314	0	1
Income	414,730	10.94	0.428	9.734	12.78
Wealth	414,730	12.07	0.615	7.212	14.29
Gender	414,730	0.802	0.399	0	1
Age	414,730	44.94	15.87	20	78
Marital status	414,730	0.589	0.463	0	1
Dependents	414,730	1.898	1.491	0	7
Firm size	414,730	12.89	0.440	9.960	14.37
Leverage	414,730	0.206	0.124	0.123	0.831
ROA	414,730	0.079	0.100	-0.409	0.583
Cash	414,730	0.080	0.033	0.066	0.255
Credit score	414,730	0.652	0.604	-0.773	3.500
Applications	414,730	6.833	1.464	1	9
Granted	137,321	0.845	0.370	0	1
Default	414,730	0.017	0.098	0	1
Loan amount	137,321	3.509	1.988	0.686	11.41
Loan spread	114,641	340.7	246.1	33.45	985.7
Maturity	137,321	47.9	37.29	4	278
Loan provisions	114,641	0.407	0.451	0	1
Collateral	114,641	0.695	0.499	0	1
Regional education (university)	414,730	0.496	0.285	0.388	0.594
Regional education (professional)	414,730	0.193	0.087	0.125	0.256
Application probability	414,730	0.259	0.027	0.140	0.611

Table 3. Means of key variables by level of educational attainment

The table reports the means for key variables of the model per incremental level of educational attainment. In the last lines are reported the shares of the individuals in each level of educational attainment to the total sample and to the sample of the individuals who were granted the loan. The variables are defined in Table 1.

	Below secondary	**Secondary**	**Post-secondary/ non-Tertiary**	**Tertiary**	**MSc**	**PhD/MBA**
Apply	0.291	0.326	0.328	0.335	0.345	0.348
Income	10.525	10.864	11.946	10.978	10.990	11.000
Wealth	11.722	12.001	12.076	12.102	12.112	12.123
Gender	0.788	0.799	0.802	0.804	0.802	0.803
Age	44.413	44.913	44.937	44.957	44.963	44.928
Marital status	0.592	0.589	0.588	0.589	0.590	0.585
Dependents	1.887	1.893	1.904	1.896	1.847	1.820
Firm size	12.871	12.888	12.896	12.895	12.897	12.905
Leverage	0.201	0.205	0.206	0.207	0.207	0.207
ROA	0.075	0.078	0.079	0.080	0.079	0.080
Cash	0.077	0.079	0.080	0.080	0.080	0.080
Credit score	0.397	0.591	0.655	0.687	0.708	0.729
Applications	6.706	6.813	6.830	6.853	6.843	6.877
Granted	0.820	0.829	0.836	0.861	0.868	0.875
Default	0.018	0.019	0.017	0.017	0.017	0.016
Loan amount	0.763	3.345	3.528	3.601	3.618	3.646
Loan spread	355.32	350.14	352.19	340.20	330.88	331.72
Maturity	43.560	47.454	47.020	47.775	48.042	49.227
Loan provisions	0.465	0.415	0.413	0.407	0.383	0.339
Collateral	0.642	0.695	0.710	0.709	0.608	0.613
Share in the sample (all applications)	0.003	0.143	0.220	0.415	0.110	0.109
Share in the sample (granted)	0.003	0.147	0.224	0.411	0.108	0.106

Table 4. Higher education and probability of loan application

The regressions examine the effect of higher education (HE) or MBA/PhD education on the probability to apply for a loan. The table reports coefficient estimates and standard errors (in parentheses) clustered by individual. Dependent variable is the binary variable *Apply*, and all variables are defined in Table 1. Specifications 1 and 3 are estimated with OLS, and specifications 2 and 4 with 2SLS. *Regional education* is the instrumental variable in specifications 2 and 4 and its effect in the first stage is given after the second-stage results. The lower part of the table denotes the fixed effects, number of observations, and adjusted R-squared (if applicable). The ***, **, and * marks denote statistical significance at the 1%, 5%, and 10% levels.

	1	**2**	**3**	**4**
Dependent variable:	Apply	Apply	Apply	Apply
Higher education	0.018***	0.034***		
	(0.002)	(0.007)		
MBA/PhD education			0.024***	0.043***
			(0.002)	(0.008)
Income	0.034***	0.025***	0.034***	0.027***
	(0.003)	(0.005)	(0.003)	(0.004)
Wealth	-0.021***	-0.021***	-0.021***	-0.021***
	(0.002)	(0.002)	(0.002)	(0.002)
Gender	0.010***	0.010***	0.010***	0.011***
	(0.002)	(0.002)	(0.002)	(0.002)
Age	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Dependents	0.001*	0.001**	0.001*	0.001**
	(0.000)	(0.000)	(0.000)	(0.000)
Firm size	0.036***	0.036***	0.036***	0.036***
	(0.002)	(0.002)	(0.002)	(0.002)
Firm leverage	0.285***	0.287***	0.285***	0.283***
	(0.034)	(0.035)	(0.034)	(0.035)
Firm ROA	0.005	0.006	0.005	0.006
	(0.010)	(0.010)	(0.010)	(0.010)
Firm cash	-2.398***	-2.472***	-2.393***	-2.413***
	(0.340)	(0.344)	(0.340)	(0.344)
Past applications	-0.000	-0.000	-0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)
First stage				
Regional education		0.212***		0.117***
		(0.078)		(0.032)
Observations	414,730	414,730	414,730	414,730
R-squared	0.56		0.56	
Year fixed effects	Yes	Yes	Yes	Yes
Individual fixed effects	Yes	Yes	Yes	Yes

Table 5. Higher education and probability of loan origination

The first two specifications examine the effect of higher education (HE) on the probability that a loan is granted by the bank (originated). Specifications 3 and 4 examine the equivalent effect on the applicant's credit score. The table reports coefficient estimates and standard errors (in parentheses) clustered by individual. All variables are defined in Table 1. Specifications 1 and 3 are estimated with OLS, and specifications 2 and 4 with 2SLS. *Regional education* is the instrumental variable in specifications 2 and 4 and its effect in the first stage is given after the second-stage results. The lower part of the table denotes the fixed effects, number of observations, and adjusted R-squared (if applicable). The ***, **, and * marks denote statistical significance at the 1%, 5%, and 10% levels.

	1	**2**	**3**	**4**
Dependent variable:	Granted	Granted	Credit score	Credit score
Higher education	0.007***	0.010**	0.018***	0.031***
	(0.002)	(0.005)	(0.002)	(0.004)
Income	0.229***	0.229***	0.627***	0.626***
	(0.005)	(0.006)	(0.004)	(0.005)
Wealth	0.017***	0.017***	0.034***	0.034***
	(0.003)	(0.003)	(0.002)	(0.002)
Gender	-0.005*	-0.005*	-0.005**	-0.005**
	(0.003)	(0.003)	(0.002)	(0.002)
Age	0.000	0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Dependents	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Firm size	0.004*	0.004*	0.003	0.004*
	(0.002)	(0.002)	(0.002)	(0.002)
Firm leverage	-0.239***	-0.239***	-0.371***	-0.370***
	(0.046)	(0.046)	(0.038)	(0.038)
Firm ROA	0.042***	0.042***	0.107***	0.107***
	(0.014)	(0.015)	(0.012)	(0.012)
Firm cash	1.013**	1.312**	1.577***	1.569***
	(0.409)	(0.660)	(0.419)	(0.420)
Past applications	0.058***	0.058***	0.053***	0.053***
	(0.001)	(0.001)	(0.001)	(0.001)
First stage				
Regional education		0.201***		0.212***
		(0.063)		(0.078)
Observations	137,321	137,321	414,730	414,730
R-squared	0.56		0.56	
Year fixed effects	Yes	Yes	Yes	Yes
Individual fixed effects	Yes	Yes	Yes	Yes

Table 6. MBA/PhD education and probability of loan origination

The first two specifications examine the effect of MBA/PhD education on the probability that a loan is granted by the bank (originated). Specifications 3 and 4 examine the equivalent effect on the applicant's credit score. The table reports coefficient estimates and standard errors (in parentheses) clustered by individual. All variables are defined in Table 1. Specifications 1 and 3 are estimated with OLS, and specifications 2 and 4 with 2SLS. *Regional education* is the instrumental variable in specifications 2 and 4 and its effect in the first stage is given after the second-stage results. The lower part of the table denotes the controls used (as in Table 4), fixed effects, number of observations, and adjusted R-squared (if applicable). The ***, **, and * marks denote statistical significance at the 1%, 5%, and 10% levels.

	1	**2**	**3**	**4**
Dependent variable:	Granted	Granted	Credit score	Credit score
MBA/PhD education	0.007**	0.016***	0.025***	0.056***
	(0.003)	(0.005)	(0.003)	(0.015)
First stage				
Regional education		0.125***		0.117***
		(0.033)		(0.032)
Observations	137,321	137,321	414,730	414,730
R-squared	0.56		0.56	
Controls	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Individual fixed effects	Yes	Yes	Yes	Yes

Table 7. Higher education and probability to reapply after rejection

The regressions examine the effect of higher education (HE) or MBA/PhD education on the probability to reapply for a loan one or two years after facing a rejection from the bank. The table reports coefficient estimates and standard errors (in parentheses) clustered by individual. Dependent variable is the binary variable *Reapply*, and all variables are defined in Table 1. All specifications are estimated with 2SLS. *Regional education* is the instrumental variable and its effect in the first stage is given after the second-stage results. The lower part of the table denotes the controls used (as in Table 4), fixed effects, and number of observations, The ***, **, and * marks denote statistical significance at the 1%, 5%, and 10% levels.

	1	**2**	**3**	**4**
Dependent variable:	Reapply	Reapply	Reapply	Reapply
Higher education	0.025**	0.030**		
	(0.012)	(0.013)		
MBA/PhD education			0.020*	0.024*
			(0.011)	(0.013)
First stage				
Regional education		0.191***		0.128**
		(0.063)		(0.058)
Observations	21,284	21,284	21,284	21,284
Controls	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Individual fixed effects	Yes	Yes	Yes	Yes

Table 8. Loan amount, spread, and collateral

The table reports coefficient estimates and standard errors clustered by individual (in parentheses) from the estimation of equations for loan amount, loan spread, and collateral; the dependent variable is noted on the first line of table. In Panel A, the main dependent variable is Higher education (HE) and in Panel B MBA/PhD education. All variables are defined in Table 1. Results are obtained from the sample of originated loans. The odd-numbered specifications are estimated using OLS; the even-numbered specifications are estimated using 2SLS. The lower part of the table denotes the rest of the control variables (same as in Table 3), fixed effects, number of observations, and adjusted R-squared (if applicable). The ***, **, and * marks denote statistical significance at the 1%, 5%, and 10% levels.

Panel A: University education

	1	**2**	**3**	**4**	**5**	**6**
	Loan amount	Loan amount	Loan spread	Loan spread	Collateral	Collateral
Higher education	0.0003	0.0011	-5.718**	-7.911**	0.001	-0.015
	(0.0011)	(0.0027)	(2.561)	(3.689)	(0.002)	(0.014)
First-stage results						
Regional education		0.197***		0.199***		0.197***
		(0.073)		(0.073)		(0.073)
R-squared	0.65		0.59		0.71	

Panel B: MBA/PhD education

	7	**8**	**9**	**10**	**11**	**12**
	Loan amount	Loan amount	Loan spread	Loan spread	Collateral	Collateral
MBA/PhD education	0.0018*	0.0027*	-7.193**	-9.119**	0.002	0.007
	(0.0010)	(0.0018)	(3.650)	(4.011)	(0.002)	(0.016)
First-stage results						
Regional education		0.119***		0.121***		0.119***
		(0.034)		(0.034)		(0.034)
R-squared	0.65		0.60		0.71	
Observations	114,641	114,641	114,641	114,641	114,641	114,641
Other controls	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Individual fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Table 9. Credit decision, education, and future firm outcomes

The table reports coefficients and standard errors clustered by individual (in parentheses). The dependent variable is given in the first row of the table and all variables are defined in Table 1. Estimation method is the local linear regression with triangular kernel. For each specification, we report the bias-corrected RD estimates with robust variance estimator. The *** and ** marks denote statistical significance at the 1% and 5% levels. The table includes all the control variables in Table 4.

	1	**2**	**3**	**4**	**5**	**6**
	Applicants with higher education			Applicants without higher education		
Dependent variable:	Default	Future ROA	Future leverage	Default	Future ROA	Future leverage
Granted	-0.164***	0.067***	0.013**	-0.245***	0.061***	0.008
	(0.029)	(0.015)	(0.006)	(0.031)	(0.016)	(0.006)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Individual fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	72,788	72,788	72,788	64,289	64,289	64,289

Table 10. Credit decision, education, and future income and wealth

The table reports coefficients and standard errors clustered by individual (in parentheses). The dependent variable is given in the first row of the table and all variables are defined in Table 1. Estimation method is the local linear regression with triangular kernel. For each specification, we report the bias-corrected RD estimates with robust variance estimator. The *** and ** marks denote statistical significance at the 1% and 5% levels. The table includes all the control variables in Table 4.

	1	2	3	4	5	6
	Applicants with higher education			Applicants without higher education		
Dependent variable:	Future income	Future wealth	Future pay inequality	Future income	Future wealth	Future pay inequality
Granted	0.038***	0.031***	0.016	0.021***	0.017**	0.040***
	(0.011)	(0.013)	(0.012)	(0.008)	(0.007)	(0.013)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Individual fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	72,788	72,788	72,788	64,289	64,289	64,289

Table 11. Credit decision and the role of asset intangibility

The table reports coefficients and standard errors clustered by individual (in parentheses). The dependent variable is given in the first row of the table and all variables are defined in Table 1. Estimation method is the local linear regression with triangular kernel. For each specification, we report the bias-corrected RD estimates with robust variance estimator. The *** and ** marks denote statistical significance at the 1% and 5% levels. The table includes all the control variables in Table 4.

Panel A: Effect of the credit decision on asset intangibility, R&D expenses, and patents

	1	**2**	**3**	**4**	**5**	**6**
	Applicants with higher education			Applicants without higher education		
Dependent variable:	Asset intangibility	R&D expenses	Patent dummy	Asset intangibility	R&D expenses	Patent dummy
Granted	0.112***	0.098***	0.083***	0.054	0.061**	0.007
	(0.023)	(0.015)	(0.028)	(0.031)	(0.029)	(0.023)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Individual fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	72,788	72,788	72,788	64,289	64,289	64,289

Panel B: Heterogeneous effect of the credit decision on firm and individual outcomes due to asset intangibility

	1	**2**		**3**	**4**	
	Applicants with higher education			Applicants without higher education		
	Future ROA	Future wealth		Future ROA	Future wealth	
Granted[15]	0.067***	0.031***		0.061***	0.017**	
	(0.015)	(0.013)		(0.016)	(0.007)	
	5	**6**		**7**	**8**	
Granted (with Asset intangibility control)	0.048***	0.026***		0.059***	0.016**	
	(0.016)	(0.013)		(0.018)	(0.007)	
	9	**10**		**11**	**12**	
Granted (with Pay inequality control)	0.054***	0.024***		0.055***	0.014**	
	(0.016)	(0.013)		(0.019)	(0.007)	
	13	**14**		**15**	**16**	
Granted (with Asset intangibility and Pay inequality controls)	0.035*	0.021		0.054***	0.014*	
	(0.018)	(0.014)		(0.020)	(0.008)	
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Individual fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	72,788	72,788	72,788	64,289	64,289	64,289

[15] As seen previously in Tables 10 and 11.

Figure 1. Point increments in education and probability of loan application

The figure reports coefficient estimates and confidence intervals from the estimation of the probability of loan application (as in Table 5) but including four dummy variables for Education (Education equals to 1+2, to Education equals 5).

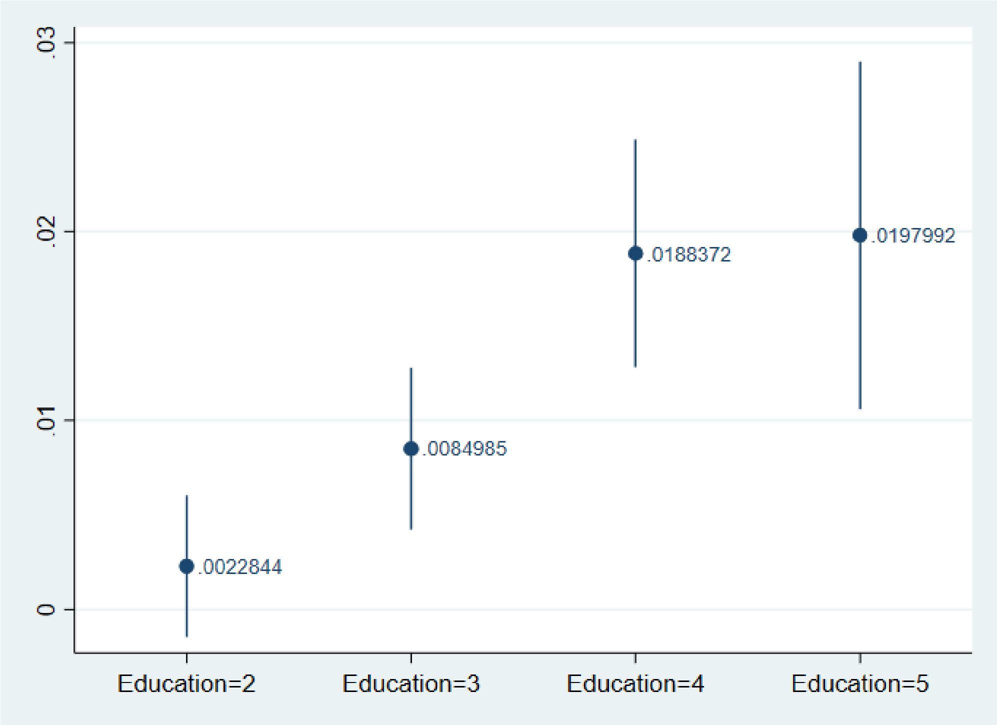
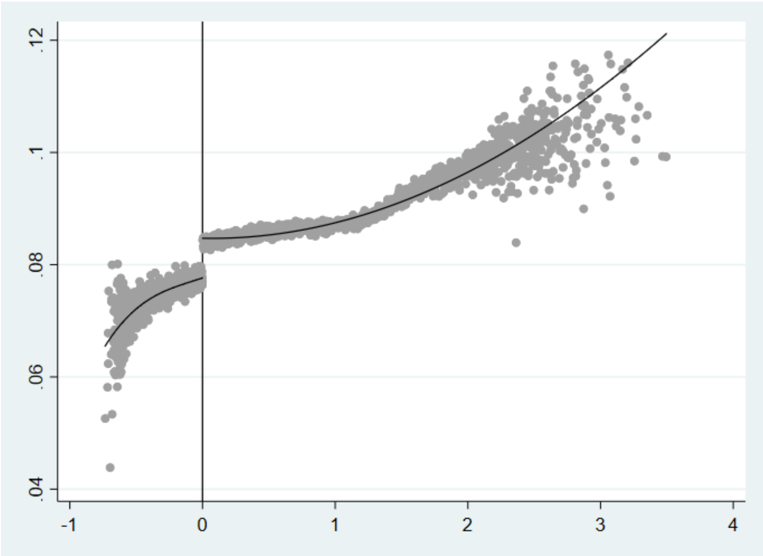
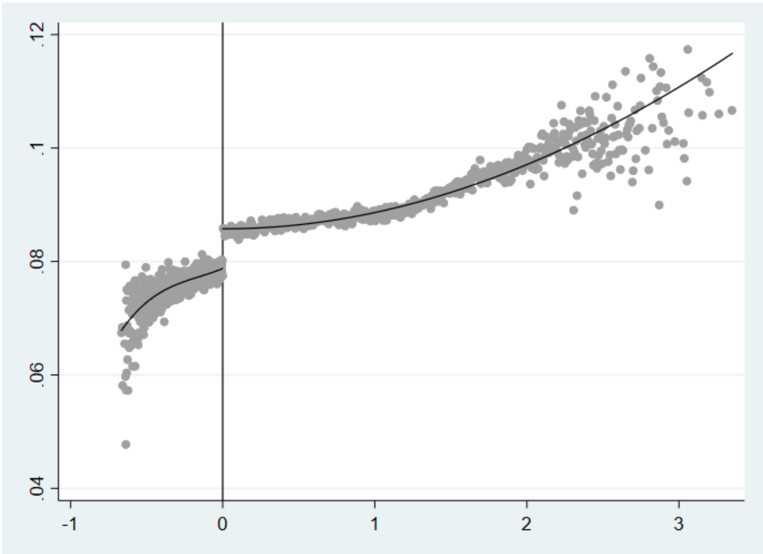
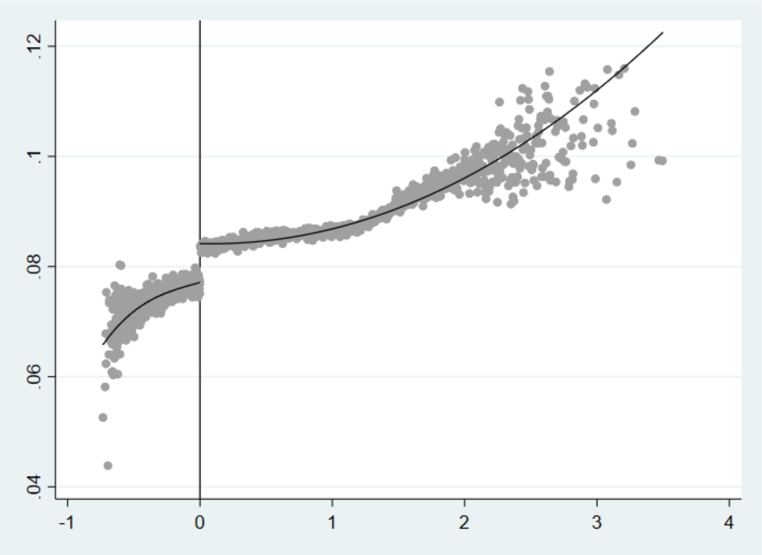


Figure 2. Response of forward ROA at the credit score's cutoff

The figures show the responses of forward ROA (y-axis) at the credit score's cutoff value (=0 on the x-axis). The figure follows Table 11. In particular, the first figure uses the full sample of loan applicants, the second is for applicants with higher education, and the third for applicants without higher education. The points represent local sample means of the applicant's income for a set of disjoint bins of control and treatment units spanning the full sample. We select evenly spaced bins that mimic the underlying variability of the data using spacings estimators. The continuous line represents a fourth order polynomial fit used to approximate the conditional mean of applicants' income below and above the cutoff.



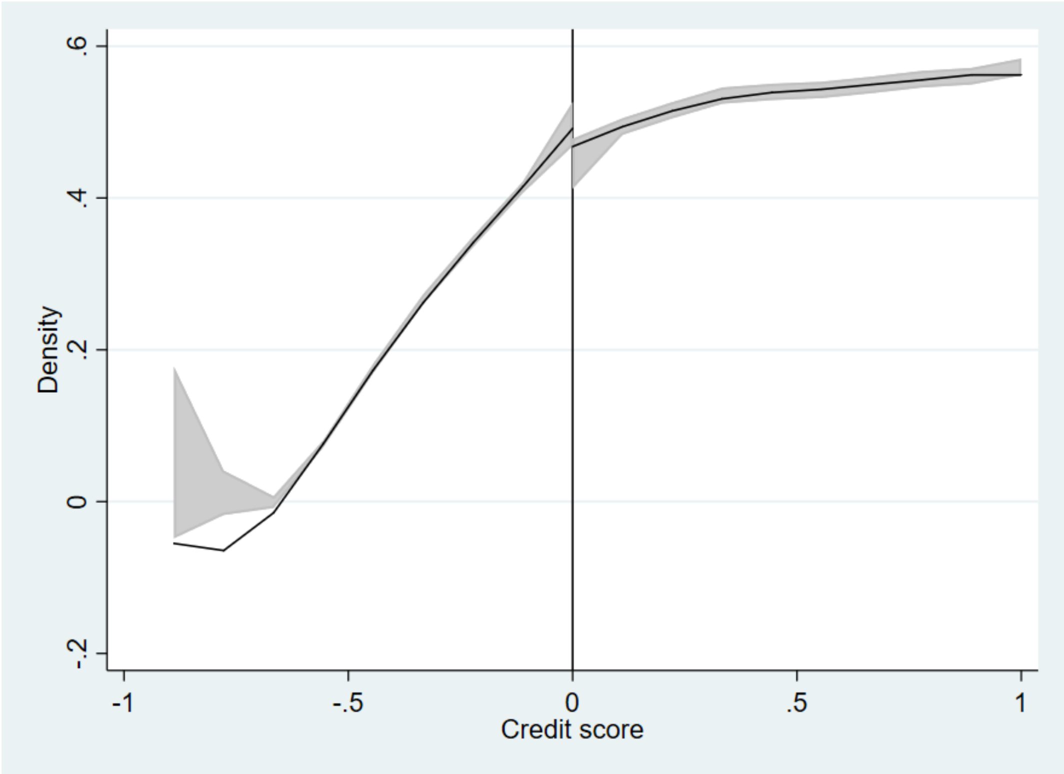




.04
.06
.08
.1
.12
-1
0
1
2
3
4

Figure 3. Manipulation test

The figure reports results from the manipulation testing procedure using the local polynomial density estimator proposed by Cattaneo et al. (2018). To perform this test, we rely on the local quadratic estimator with cubic bias-correction and triangular kernel.



Appendix
Education and Credit: The Matthew Effect

This appendix, intended for online use only, provides results without individual fixed effects (Table A1), and results with standard error clustering by region (Table A2).

Table A1. Results without individual fixed effects

This table replicates the regressions of Tables 4 to 9 in the main text without including individual fixed effects. As expected, the results typically present larger coefficients and smaller standard errors. The dependent variables are given for every regression, and all variables are defined in Table 1. The ***, **, and * marks denote statistical significance at the 1%, 5%, and 10% levels.

Replicates Table 4	**1**	**2**	**3**	**4**
Dependent variable:	Apply	Apply	Apply	Apply
Higher education	0.023***	0.043***		
	(0.001)	(0.005)		
MBA/PhD education			0.027***	0.045***
			(0.001)	(0.006)

Replicates Table 5	**1**	**2**	**3**	**4**
Dependent variable:	Granted	Granted	Credit score	Credit score
Higher education	0.013***	0.017***	0.025***	0.039***
	(0.002)	(0.004)	(0.002)	(0.003)

Replicates Table 6	**1**	**2**	**3**	**4**
Dependent variable:	Granted	Granted	Credit score	Credit score
MBA/PhD education	0.013***	0.024***	0.037***	0.073***
	(0.002)	(0.003)	(0.002)	(0.011)

Replicates Table 7	**1**	**2**	**3**	**4**
Dependent variable:	Reapply one year	Reapply one year	Reapply two years	Reapply two years
Higher education	0.034***	0.038**		
	(0.010)	(0.010)		
MBA/PhD education			0.025***	0.029***
			(0.007)	(0.011)

Replicates Table 8, Panel A, IV models	**1**	**2**	**3**
	Loan amount	Loan spread	Collateral
Higher education	0.0019	-10.372***	-0.038***
	(0.0020)	(3.011)	(0.012)
Replicates Table 8, Panel B, IV models	**4**	**5**	**6**
	Loan amount	Loan spread	Collateral
MBA/PhD education	0.0037*	-14.398***	-0.007
	(0.0017)	(3.857)	(0.016)

Replicates Table 9	**1**	**2**	**3**	**4**
Dependent variable:	Default	Default	Default	Default
Higher education	-0.007***	-0.009***		
	(0.0014)	(0.0010)		
MBA/PhD education			-0.006***	-0.009***
			(0.0011)	(0.0013)

Table A2. Clustering at the regional level

This table replicates the regressions of Tables 4 to 9 in the main text using regional-level clustering. This might be important especially for the IV regressions for which the instrument is observed at the regional level. The dependent variables are given for every regression, and all variables are defined in Table 1. The lower part of the table denotes the fixed effects, number of observations, and adjusted R-squared (if applicable). The ***, **, and * marks denote statistical significance at the 1%, 5%, and 10% levels.

Replicates Table 4	**1**	**2**	**3**	**4**
Dependent variable:	Apply	Apply	Apply	Apply
Higher education	0.018***	0.034***		
	(0.003)	(0.008)		
MBA/PhD education			0.024***	0.043***
			(0.002)	(0.009)
Replicates Table 5	**1**	**2**	**3**	**4**
Dependent variable:	Granted	Granted	Credit score	Credit score
Higher education	0.007***	0.010**	0.018***	0.031***
	(0.001)	(0.005)	(0.003)	(0.006)
Replicates Table 6	**1**	**2**	**3**	**4**
Dependent variable:	Granted	Granted	Credit score	Credit score
MBA/PhD education	0.007**	0.016***	0.025***	0.056***
	(0.003)	(0.006)	(0.004)	(0.017)
Replicates Table 7	**1**	**2**	**3**	**4**
Dependent variable:	Reapply one year	Reapply one year	Reapply two years	Reapply two years
Higher education	0.025**	0.030**		
	(0.011)	(0.014)		
MBA/PhD education			0.020*	0.024*
			(0.010)	(0.013)
Replicates Table 8, Panel A, IV models	**1**	**2**	**3**	
	Loan amount	Loan spread	Collateral	
Higher education	0.0011	-7.911**	-0.015	
	(0.0029)	(3.730)	(0.015)	
Replicates Table 8, Panel B, IV models	**4**	**5**	**6**	
	Loan amount	Loan spread	Collateral	
MBA/PhD education	0.0027*	-9.119**	0.007	
	(0.0018)	(4.188)	(0.020)	
Replicates Table 9	**1**	**2**	**3**	**4**
Dependent variable:	Default	Default	Default	Default
Higher education	-0.005***	-0.006***		
	(0.0026)	(0.0020)		
MBA/PhD education			-0.005***	-0.007***
			(0.0017)	(0.0022)