UCD CENTRE FOR ECONOMIC RESEARCH

WORKING PAPER SERIES

2022

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WP22/14

April 2022

UCD SCHOOL OF ECONOMICS
UNIVERSITY COLLEGE DUBLIN
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DUBLIN 4

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For valuable comments and suggestions, we thank Hans Degryse, Paul Devereaux, Ben Elsner, Stefanie Haller, Seamus McGuinness, Oana Peia, Karl Whelan, and seminar participants at University College Dublin (UCD), the Economic and Social Research Institute (ESRI), the Irish Economics Association (IEA), Beijing University of Technology, 5th Benelux Banking Research Day (KU Leuven), RCEA Conference on Recent Developments in Economics, Econometrics and Finance (Rimini Centre for Economic Analysis), and 7th LEER Conference on Education Economics (KU Leuven).

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Education and Credit: A Matthew Effect

Abstract

Using a unique corporate loans dataset for entrepreneurs with small and microenterprises, this paper examines how educational attainment affects bank credit decisions and subsequent individual and firm outcomes. Our results highlight a "Matthew Effect," where an initial advantage is self-amplifying. We find that entrepreneurs who obtain university education are more likely to apply for credit, and receive higher credit scores, and better lending terms. Via this credit channel, such entrepreneurs have significantly better future firm outcomes compared to those without a 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 education more likely to apply for business loans, and if so, do they have higher chances of getting those loans? Following a 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. Accordingly, if education level plays a role in decisions to apply for credit and grant credit, it 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 become more innovative, more profitable, and larger. These effects are especially important for small firms that 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 firms and micro firms, following the relevant definition from the European Commission (total assets less than €10 million). We observe repeated loan applications from the same applicants and construct a balanced panel dataset over 2002-2018. Our final dataset includes 137,321 loan applications from 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.; we also have data on firm characteristics (including 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 how education affects the probability of applying for credit, and we analyze whether the bank grants the loans and under what terms. At this stage, we also consider how education affects reapplication if the bank rejects a loan application. 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 influences the credit channel's effect on 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 scores, 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 oriented more toward 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" via the credit channel.[1,2] This term refers to a cumulative advantage, where obtaining higher education increases the probability of applying for a loan (by approximately 3.4 percentage points), having a higher credit score (3.1 percentage points), and reapplying for a loan within one year if rejected (3 percentage points). Moreover, applicants with higher education face loan spreads that are 7.9 basis points lower. When we consider applicants with professional education (an MBA and/or a Ph.D.), these results become even more vigorous, potentially due to 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 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 with applicants who have higher education are less likely to default within three years after a loan origination compared to firms with non-higher-education applicants. Subsequently, using our RDD framework and depending on higher education attainment, we find that a positive credit decision from 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). Importantly, these

[1] Sociologist Robert K. Merton coined the term "Matthew Effect" 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 on we refer to two groups: higher education (i.e., those with higher educational qualifications such as tertiary, MSc, MBA, and Ph.D. degrees) and non-higher-education (i.e., those without higher educational qualifications such as secondary, postsecondary, and nontertiary education).

effects are more pronounced for the professional education group of entrepreneurs. These findings show that the effects identified in 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 from 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 (and even higher for those with professional education). Last, we show that asset intangibility and investments in high-skilled labor (low within-firm inequality) almost fully explain how a positive credit decision from the bank affects the future returns and wealth of entrepreneurs with higher and professional education. 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 that credit origination has on future firm performance and entrepreneurs' wealth. This finding is consistent with Acemoglu (1999) and Song et al. (2019), who suggest that due to technological advancements, firms with rising returns to skill hire higher-paid employees compared to firms with lower returns to skill.

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

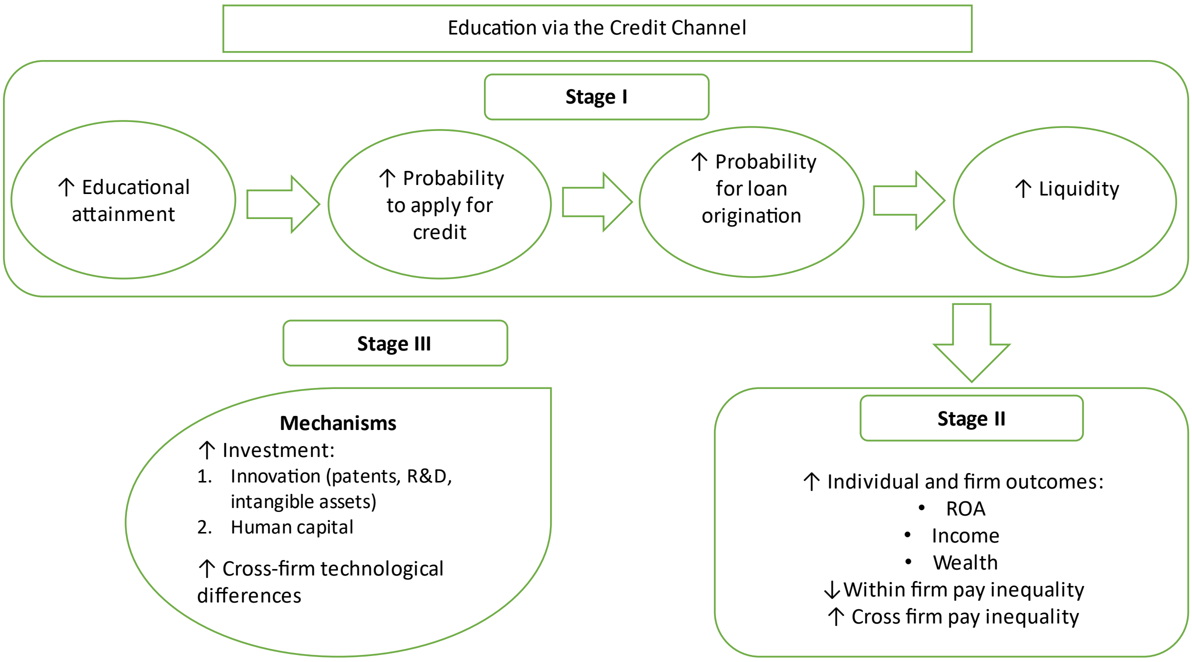
The credit channel operates as follows: loan origination generates liquidity, which leads to more investment, which increases firm profitability, which increases entrepreneurs' future wealth and income. Theoretically, different levels of educational attainment can affect the investment and managerial 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 the bank's decision to grant the loan.

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

Stage III: How firms use the increased liquidity for investment influences the effects identified in stage I and stage II.

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 signal ability of the loan applicant, affecting the bank's 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 applicant's educational attainment in the credit score. This enables higher-education applicants to earn higher credit scores, increasing their chances of loan origination and credit access (Becker, 1993; Spence, 1973; Goodman et al., 2017).

Terms of lending: Due to higher levels of human capital development, higher-education applicants better understand the loan-origination process, have 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 different levels of education make different managerial and investment decisions to exploit the increased liquidity after loan origination. Cross-firm technological differences may affect these decisions, 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, entrepreneurs with higher education invest more in 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 decrease within-firm pay inequality after loan origination, increasing segregation of high-wage employees at firms investing in higher innovation (Song et al., 2019).

2.4. Relation to the extant literature

To our knowledge, our paper is the first to connect 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 how the credit channel affects 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 background (education and wealth) to future financial health, showing that education plays an important role in credit score formation. Papadimitri et al. (2020) find that higher education within a firm's board of directors positively affects credit ratings. Marilanta and Nurmi (2018) and Lin et al. (2011) show how educational attainment among entrepreneurs affects their firm's performance.

Second, a substantial amount of literature documents the interplay between technology and education in firm performance. Technological changes affect inequality due to labor demand shifts toward 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 one another (increased "segregation"). Song et al. (2019) observe a rise in earnings inequality in the United States and attributes one-third of that rise to within-firm pay inequality and two-thirds to cross-firm 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 education levels positively affect the entrepreneurial self-efficacy index. 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 financial development.

3. Data

There is 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 applying for loans from 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 European Banking Authority (EBA) definition. We have access to its full loan portfolio, applications, originations, and rejections from 2002 to 2018.[3] Similar to Delis et al. (2020), we focus on the use of data for loans to domestic small firms and micro firms (total assets of up to €10,000,000 per the EU definition). The bank operates on a global scale and

[3] Delis et al. (2020) use a similar data set; 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.

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 firms 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 loan, including the bank's loan decision (approved or rejected). Importantly, we have access to the applicant's credit score upon which the bank conditions its decision. We also know whether the applicant has an exclusive relationship with the bank.[4] The bank records which firms apply for loans from 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 outcomes. Using these data and repeat loan applications from the same applicants, we construct a panel data set of loan applicants over the period 2002–2018.

For most applicants, we observe more than one loan application during our sample period. To compare individuals, it is necessary to observe firm and applicant characteristics at two or more points in time. Thus, we maintain a firm-year balanced panel data set. We discard loans to applicants who never reapply for loans. Essentially, all individuals reapply for loans

[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, Berger et al. (2011) document a 71% exclusive relationship between banks and SMEs in three European countries (Germany, Italy, and the UK), but this is less often the case in the United States (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 northern European countries. Farinha and Santos (2002) report similar statistics for Portugal (70% of firms with fewer than 10 employees have one bank relationship). More recently, Bonfim at al. (2018) report a mean value of two banks for small Portuguese firms, but the Portuguese banking sector is much less concentrated than 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.

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 arrives in the future, the bank requests information about applicants' income and wealth retrospectively. Using this information, we generate a panel dataset of 138,633 loan applications by 24,712 unique applicants from 2002 to 2018. From these loan applications, 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, region, and industry. At the loan level, we observe the loan characteristics (i.e., spread, amount, maturity, and collateral).

We define all the variables used in our analysis in Table 1 and 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.

[Please insert Tables 1 & 2 about here]

[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-size firms.

3.2. Key variables

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

Table 3 reports summary statistics separately for *Education* and provides a first indication of a "Matthew effect" (i.e., a significant increase in the probability of applying for a loan, increased credit scores, and better firm outcomes as *Education* increases). Also, we observe that entrepreneurs with higher education (university degree and above) get better loan terms (i.e., amount, spread, maturity, and provisions) and their firms are less likely 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) postsecondary/nontertiary; (iii) tertiary and MSc; and (vi) MBA or Ph.D. We observe a positive relationship between the probability of receiving a loan application and educational attainment. We observe the most significant increase when comparing higher education to nonhigher education applicants.

[Please insert Figure 1 about here]

Credit score is a statistical tool financial institutions construct to determine the credit health of an individual or a firm. In our panel, *Credit score* ranks the entrepreneurs' credit risk; banks use it to decide whether to extend or deny credit, as well as the lending terms. If a credit

[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.

score is above a specific cutoff point, the bank originates the loan; if a credit score is below this cutoff, the bank denies the loan (or suggests reexamination later). We are not permitted to disclose the precise cutoff, therefore we normalize it to zero.

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 variables such as *Gender, Age, Income*, *Wealth, Marital status,* or *Dependents.* For example, previous research finds that males are more likely to apply for credit than females. Also, entrepreneurs who are younger (on average), married, and with fewer dependents are also more likely to apply for 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). *Intangible assets* is the ratio of intangible assets to total assets. *R&D expenses* is 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 reapplication after rejection. Also, we examine how education affects loan origination and lending terms (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 individual *i* in our sample applies for a loan in year *t* (and 0 otherwise). *Granted* is a binary variable equal to 1 if the bank originates the loan (i.e., the credit score is positive) and 0 if the bank rejects the loan application (i.e., the credit score is negative). *Credit score* is a continuous variable normalized around 0, which is the value above (below) which the bank grants (rejects) the loan application. *Higher education* is a dummy variable that takes the value 1 if the individual (*i*) has completed higher (tertiary) 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/Ph.D.) and the value 0 if that individual has not completed any higher education. 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., 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 in different years renders the probability of significant correlation of *Higher education* with other individual characteristics unobserved to the bank 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 in 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 *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) degrees to total entrepreneurs by region, industry, and year, 15 years prior each loan application. For example, the value for the share in 1990 is the instrument for the loans originated in 2005.

The literature extensively uses historical regional instruments (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 in that region is to have a highly educated entrepreneur now. Although 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 we 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 of applying for a loan (1.8 percentage points). This becomes 2.4 percentage points for applicants with a professional education (MBA/Ph.D.), as reported in column 3.[9]

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 *Professional education* (column 4). Specifically, a one-

[8] In alternative specifications we also cluster on the regional level. This might be important especially for the IV regressions for which we observe the instrument 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 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 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.

standard-deviation increase in *Regional education* is associated with a 21.2 percentage-point increase in the probability that the loan applicant has higher education (statistically significant at the 1% level). This is intuitive, given that the preexistence (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 increases the probability of applying for a loan by 3.4 percentage points. Again, we find stronger estimates when considering the effect of *Professional 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., a 2.3 percentage-point increase in the probability of applying for those with higher education, and a 4.3 percentage-point increase for those with a 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]

The first four specifications of Table 5 report the results, showing a statistically significant effect of *Higher education* on both *Granted* (first two columns) and *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 get a loan. The equivalent results in column 4 show that applicants obtaining higher education have credit scores that are 3.1 percentage points higher. These results effectively show how much the bank values higher education in its credit scoring system.

Along the same line, the last four specifications of Table 5 show that individuals obtaining professional education have a 1.6 percentage-point higher probability of getting the loan (results in column 2). When we use *Credit score* as our dependent variable, the results in column 4 suggest that individuals obtaining *Professional education* have credit scores that are 5.6 percentage points higher than the nonprofessional 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 reapply for a loan sooner. To this end, we reestimate equation 1 with the dummy dependent variable *Reapply*, which takes the value 1 for the rejected applicants who reapply for a loan within one or two years after the bank's credit decision (value equals 0 for those who did not reapply).[10] For this exercise, we use the sample of rejected applicants (21,284 observations).

Columns 1 and 2 of Table 6 report OLS estimations for a model where the base cases are individuals with no higher education and no professional education respectively, whereas columns 3 and 4 report the equivalent 2SLS estimations.[11] We use a one-year window in columns 1 and 3, and we use a two-year window in columns 2 and 4. The results show applicants with higher educations have a higher probability of reapplying 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

[10] We also know that those applicants did not reapply for credit from another bank (at least at banks 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.

one-year (two-year) window after the original rejection. Interestingly, these probabilities do not increase for rejected applicants with professional education. In particular, rejected applicants with professional education have a 2% (2.4 %) higher probability of reapplying within a 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 6 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 of Table 7 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* (column 4) suggest that individuals obtaining higher education face spreads that are eight basis points lower compared to those without higher education. We may explain this result both from the entrepreneur's side (demand effect), in which individuals with higher education can better negotiate lending terms, and from the bank's side (supply effect), in which banks directly consider individuals with higher education a less risky investment.

[Please insert Table 7 about here]

Interestingly, considering individuals obtaining professional education in panel B, we find that apart from a statistically significant effect on the loan spread, those individuals get loans that are 2.7% larger (statistically significant at the 10% level). An increase in the negotiation power of these individuals and/or the nature of their projects, which might be more expensive and technologically sophisticated, may potentially explain this result.

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 loans 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 correlate with regional dynamics.

A solution to this identification problem comes from the dichotomy between the bank granting or not granting the loan (*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 investment, which in turn increases profitability and decreases the probability of default. The key assumption for the validity of this RDD design is that applicants cannot consistently and precisely manipulate their credit scores, because the bank is a value-maximizing entity aiming to minimize nonperforming loans.

To this end, we estimate the following model:

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

Forward outcome is either *Default*, *Forward ROA*, *Forward leverage*, *Future pay inequality*, and individual *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 to higher education and nonhigher 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 (Cattaneo et al., 2021).[12] We use a nonparametric local linear regression, which has the advantage of assigning higher weights to observations closer to the cutoff value of 0. 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 *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' incomes below and

[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 flexibility, 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 (results in Appendix Table A3).

[13] Essentially, these represent the "interesting" bins as selected by the software and not the full set of observations.

above the cutoff. All the figures show clear upward shifts in *Forward ROA*. This suggests that the treatment (*Granted* = 1) entails a sharp discontinuity in both the outcome 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 nonlinearity.

[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 8. 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 8); this also implies that the approach is less sensitive to differences 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 *Default, Future ROA*, and *Future leverage* for individuals with a higher education. Columns 4 to 6 present the equivalent for individuals without higher education; columns 7 to 9 report the results for individuals with professional education.

[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.

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 percentage points. This eight-point difference is highly statistically significant (at the 1% level) and suggests that applicants without higher education rely much more on loan origination to avert default. Considering applicants with professional education, this difference is even higher at 9.5 percentage points. These findings are fully consistent with our stage I analysis, whereby entrepreneurs with higher and professional education are more likely to apply for a loan (or reapply after being rejected) and get it.

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 (professional) education by 0.06 (0.16) points more than for applicants without higher (professional) 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 groups. Entrepreneurs with higher education are more willing to increase *Future leverage*, with the effect being statistically and economically significant; leverage increases by 1.3 percentage points and is statistically significant (at the 5% level). In contrast, the effect is statistically insignificant for those without higher education. This picture is even more pronounced comparing entrepreneurs with professional education with entrepreneurs without higher education.

[Please insert Table 8 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 owners compared to the rest of the employees (within-firm pay inequality). We have two ways to capture this wage inequality. First, we observe whether education affects individual *Future* *income* and *Wealth* through the credit channel. Second, we examine how different levels of education affect the future within-firm *Pay inequality*. Results are in Table 9. Once again, we estimate equation 4 for applicants with and without higher education, as well as for applicants with professional education. The dependent variable for columns 1 and 3 is *Future income*; for columns 2 and 4 is *Future wealth*; and for columns 3 and 6 is *Future pay inequality*.

[Please insert Table 9 about here]

We find that a positive credit decision from the bank leads to a 3.8 (5)-percentage-point increase in income for entrepreneurs with higher (professional) education, whereas the equivalent effect for the applicants without higher education is 2.1 percentage points. Similar differences are observed for *Future wealth*, which is 1.4 (3.5) percentage points higher for those with higher (professional) 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 closer to their own. We find that loan origination has no significant effect on within-firm pay inequality for entrepreneurs with higher education, whereas the effects are statistically and economically significant for 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 in 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 in their employees' wages, reducing within-firm pay inequality. These effects might be even more potent considering entrepreneurs with professional education.

To pinpoint these mechanisms, first we reestimate 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 for *Granted*.

6.2. Results

Table 10 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 entrepreneurs with higher education hire employees at wages similar to their own. To further explain this finding, we examine whether entrepreneurs with higher education 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 column 1 of panel A, we first show that entrepreneurs with higher education who got loans invest, on average, 11 percentage points more in intangible assets than applicants with higher education who did not get a loan. In column 7, the equivalent effect for entrepreneurs with professional education is 13 percentage points. In contrast, the effect for the less educated entrepreneurs (column 4) is statistically insignificant. Also, when we take the difference of the coefficients between columns 1 and 4, we find that entrepreneurs with higher education invest, on average, 11 percentage points more in intangible assets (the coefficient for nonhigher education entrepreneurs in column 4 is statistically insignificant).

Similarly, the results in columns 3 and 6 of panel A 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 a 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 toward innovation after a loan origination. The effect of loan origination on *R&D expenses* is positive for entrepreneurs with and without higher education, but again the effect is stronger for the higher-education group (10 percentage points versus 6 percentage points, respectively). Importantly, the equivalent differences between the professional education and no tertiary education groups are even more pronounced, which pinpoints that moving to higher and more sophisticated forms of education explains firm performance-related outcomes via the credit channel.

[Please insert Table 10 about here]

Next, we examine how *Granted* affects firm and individual outcomes (Table 10, 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*. In specifications 1 to 6, we first replicate the results in Tables 8 and 9 for illustrative purposes. Next, in specifications 7 to 18, we find that sequentially adding these controls significantly lowers the impact of *Granted* on *Future ROA* and *Future wealth* for the higher-education entrepreneurs and the professional-education entrepreneurs. Adding both controls (specifications 19 to 24) accounts for almost all the statistically significant impact of *Granted* in the higher-education and professional-education groups. For higher education, the relevant coefficient falls 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 19 and 20 are barely statistically significant at the 10% level or insignificant, and the original estimates without the controls in specifications 1 and 2 are statistically significant at the 1% level. The results draw a very similar picture for the entrepreneurs with professional education (specifications 23 and 24).

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 via the credit channel, whereby investment in intangible assets and high-quality employees play a key role.

7. Conclusions

This paper investigates how education affects entrepreneurial and bank credit decisions, as well as subsequent individual and firm outcomes, via the credit channel. Our analysis uses a unique sample of corporate bank loans to majority owners of small firms and microenterprises from a major European bank.

We find that entrepreneurs who obtain higher education are more likely to apply for credit, obtain higher credit scores, and get better lending terms. Subsequently, more highly (tertiary) educated entrepreneurs, due to their higher chances of loan approval, have significantly enhanced future firm outcomes (firm profitability, probability of default, leverage). This leads to higher future individual income and wealth. Our combined results highlight a Matthew effect, where the initial advantage of higher 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 toward technological innovation (R&D, intangible assets, and patents). Equivalently, their managerial decisions focus on investments in human capital and selecting higher-wage 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 advises against proceeding with the application, fully rejects, or only originates 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	An ordinal variable ranging between 0 and 5 if the individual completed the following education. 0: No secondary; 1: Secondary; 2: Postsecondary, nontertiary; 3: Tertiary; 4: MSc; 5: MBA or Ph.D.
Higher education	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/Ph.D. education (i.e., Education > 3) and 0 if the individual did not complete tertiary education (i.e., Education < 3).
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	0.109	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. The last lines report individuals at each level as a proportion of educational attainment for the total sample and for the sample of the individuals who were granted loans. The variables are defined in Table 1.

	Below secondary	**Secondary**	**Postsecondary/ Nontertiary**	**Tertiary**	**MSc**	**Ph.D./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	0.209	0.285	0.301	0.093	0.109
Share in the sample (granted)	0.003	0.197	0.248	0.338	0.108	0.106

Table 4. Higher education and probability of loan application

The regressions examine how *Higher education* or *Professional education* affects the probability of applying 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 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)		
Professional 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	251,326	251,326
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 table reports coefficient estimates and standard errors (in parentheses) clustered by individual. All variables are defined in Table 1. The first two specifications examine the effect of *Higher education* on the probability that a bank grants a loan. Specifications 3 and 4 examine the equivalent effect on the applicant's credit score. Specifications 5 and 6 examine the effect of *Professional education* on the probability that a bank grants a loan. Specifications 7 and 8 examine the equivalent effect on the applicant's credit score. Specifications 1, 3, 5, and 7 are estimated with OLS, and the rest with 2SLS. *Regional education* is the instrumental variable in specifications 2 and 4 and its effect in the first stage is after the second-stage results. The lower part of the table denotes the controls used (as in Table 4), 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**	**5**	**6**	**7**	**8**
Dependent variable:	Granted	Granted	Credit score	Credit score	Granted	Granted	Credit score	Credit score
Higher education	0.007***	0.010**	0.018***	0.031***				
	(0.002)	(0.005)	(0.002)	(0.004)				
Professional education					0.007**	0.016***	0.025***	0.056***
					(0.003)	(0.005)	(0.003)	(0.015)
First stage								
Regional education		0.201***		0.212***		0.125***		0.117***
		(0.063)		(0.078)		(0.033)		(0.032)
Observations	137,321	137,321	414,730	414,730	76,076	76,076	251,326	251,326
R-squared	0.56		0.56		0.56		0.56	
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 6. Higher education and probability of reapplying after rejection

The regressions examine the effect of *Higher education* or *Professional education* on the probability of reapplying 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 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)		
Professional 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	12,515	12,515
Controls	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Individual fixed effects	Yes	Yes	Yes	Yes

Table 7. 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* and in panel B *Professional education.* All variables are defined in Table 1. Results are 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: Higher education

	1	**2**	**3**	**4**	**5**	**6**
Dependent variable:	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	
Observations	114,641	114,641	114,641	114,641	114,641	114,641

Panel B: Professional education

	7	**8**	**9**	**10**	**11**	**12**
	Loan amount	Loan amount	Loan spread	Loan spread	Collateral	Collateral
Professional 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	63,053	63,053	63,053	63,053	63,053	63,053
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 8. Credit decision, education, and future firm outcomes

The table reports coefficients and standard errors clustered by individual (in parentheses). The dependent variable is on top of each regression, 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)
Observations	75,801	75,801	75,801	61,520	61,520	61,520

	7	**8**	**9**
	Applicants with professional education		
Dependent variable:	Default	Future ROA	Future leverage
Granted	-0.150***	0.077***	0.020***
	(0.038)	(0.023)	(0.006)
Observations	14,556	14,556	14,556

Table 9. Credit decision, education, and future income and wealth

The table reports coefficients and standard errors clustered by individual (in parentheses). The dependent variable is on top of each regression, 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)
Observations	75,801	75,801	75,801	61,520	61,520	61,520

	7	**8**	**9**
	Applicants with professional education		
Dependent variable:	Future income	Future wealth	Future pay inequality
Granted	0.050***	0.035***	0.021*
	(0.013)	(0.017)	(0.011)
Observations	14,556	14,556	14,556

Table 10. Higher education, credit decision, and the role of asset intangibility

The table reports coefficients and standard errors clustered by individual (in parentheses). The dependent variable is on top of each regression, and all variables are defined in Table 1. The 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. The number of observations is as in the respective parts of Tables 8 and 9 for applicants with higher education, applicants without higher education, and applicants with professional education.

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)

	7	**8**	**9**
	Applicants with professional education		
Dependent variable:	Asset intangibility	R&D expenses	Patent dummy
Granted	0.130***	0.152***	0.119***
	(0.028)	(0.029)	(0.040)

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

	Applicants with higher education		Applicants without higher education		Applicants with professional education	
	Future ROA	Future wealth	Future ROA	Future wealth	Future ROA	Future wealth
	1	**2**	**3**	**4**	**5**	**6**
Granted[15]	0.067***	0.031***	0.061***	0.017**	0.077***	0.035***
	(0.015)	(0.013)	(0.016)	(0.007)	(0.023)	(0.017)
	7	**8**	**9**	**10**	**11**	**12**
Granted (with Asset intangibility control)	0.048***	0.026**	0.059***	0.016**	0.044**	0.027**
	(0.016)	(0.013)	(0.018)	(0.007)	(0.021)	(0.012)
	13	**14**	**15**	**16**	**17**	**18**
Granted (with Pay inequality control)	0.054***	0.024***	0.055***	0.014**	0.059***	0.025**
	(0.016)	(0.013)	(0.019)	(0.007)	(0.020)	(0.011)
	19	**20**	**21**	**22**	**23**	**24**
Granted (with Asset intangib. and Pay inequality controls)	0.035*	0.021	0.054***	0.014*	0.029*	0.019
	(0.018)	(0.014)	(0.020)	(0.008)	(0.015)	(0.012)

15 As seen previously in Tables 8 and 9.

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 1+2, to *Education* equals 5).

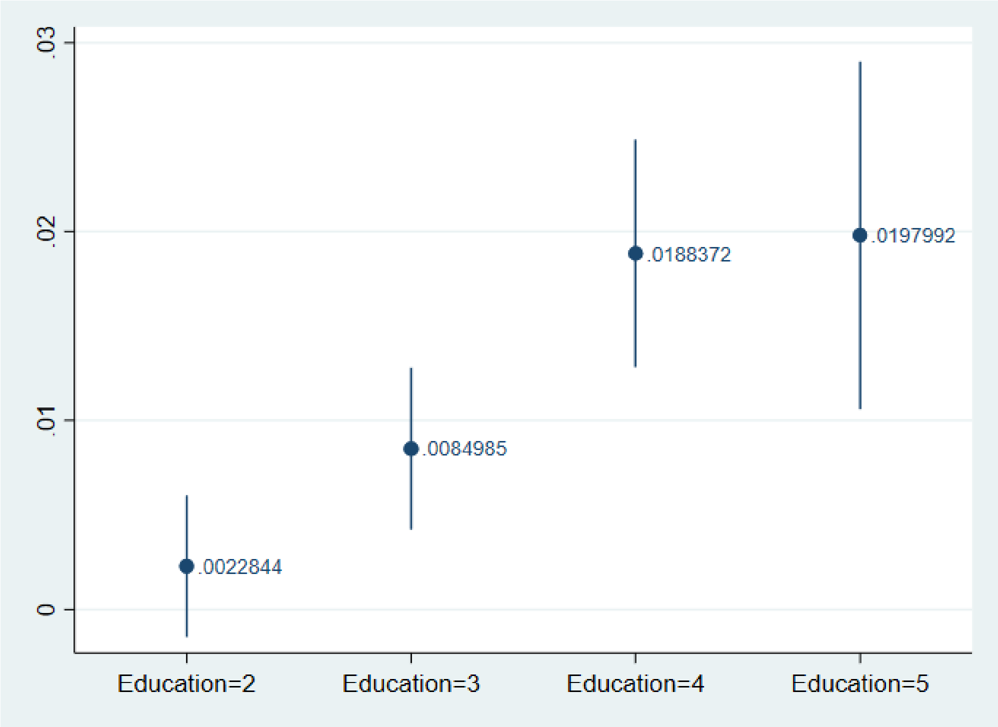
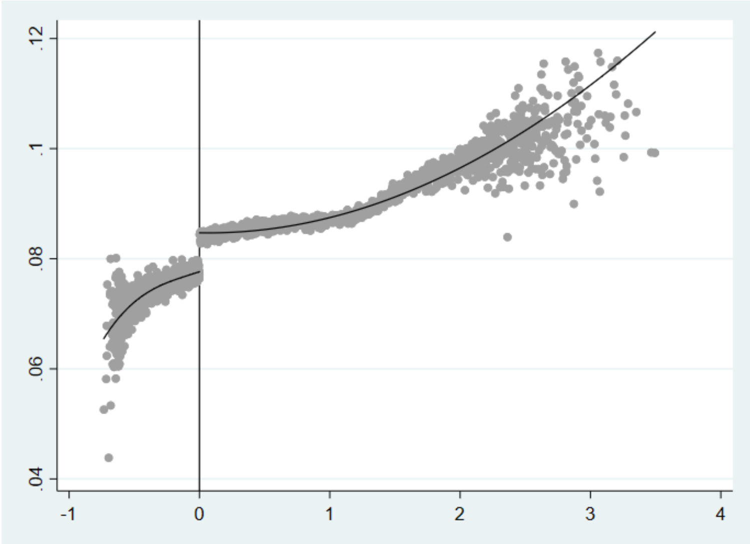
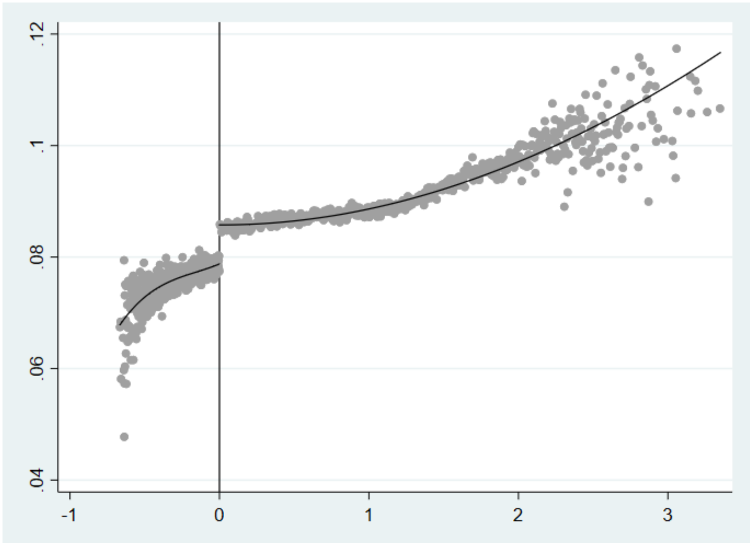


Figure 2. Response of forward ROA at the credit score's cutoff

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.





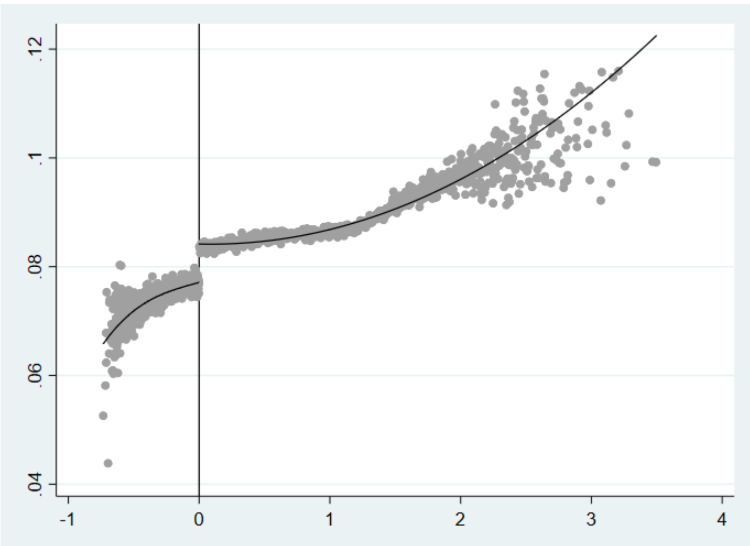
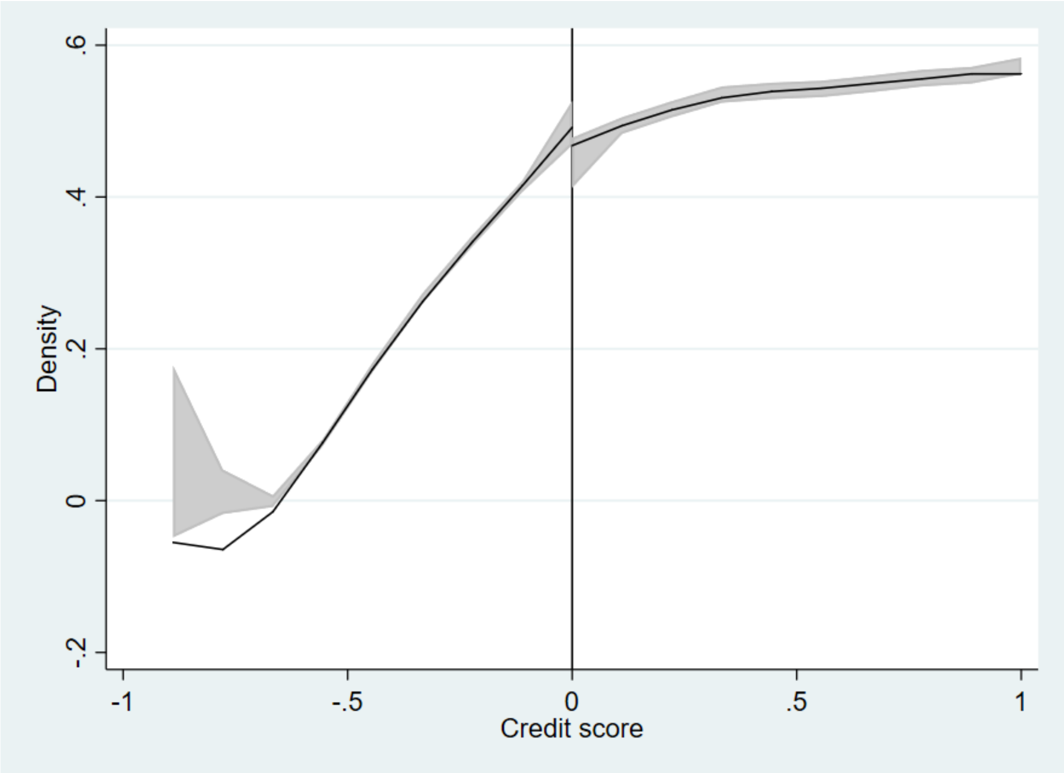


Figure 3. Manipulation test

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 additional robustness tests. Specifically, we replicate the results of Tables 4 to 7 without individual fixed effects (Table A1) and with standard error clustering by region (Table A2). Moreover, in Table A3, we replicate the results of Tables 8 and 9 using a simple OLS model with interaction terms.

Table A1. Results without individual fixed effects

This table replicates the regressions of Tables 4 to 7 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)		
Professional 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)
	5	**6**	**7**	**8**
Dependent variable:	Granted	Granted	Credit score	Credit score
Professional education	0.013***	0.024***	0.037***	0.073***
	(0.002)	(0.003)	(0.002)	(0.011)

Replicates Table 6	**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)		
Professional education			0.025***	0.029***
			(0.007)	(0.011)

Replicates Table 7, 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 7, panel B, IV models	**4**	**5**	**6**
	Loan amount	Loan spread	Collateral
Professional education	0.0037*	-14.398***	-0.007
	(0.0017)	(3.857)	(0.016)

Table A2. Clustering at the regional level

This table replicates the regressions of Tables 4 to 7 in the main text using regional-level clustering. This might be important 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)		
Professional 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)
	5	**6**	**7**	**8**
Dependent variable:	Granted	Granted	Credit score	Credit score
Professional education	0.007**	0.016***	0.025***	0.056***
	(0.003)	(0.006)	(0.004)	(0.017)

Replicates Table 6	**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)		
Professional education			0.020*	0.024*
			(0.010)	(0.013)

Replicates Table 7, 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 7, panel B, IV models	**4**	**5**	**6**	
	Loan amount	Loan spread	Collateral	
Professional education	0.0027*	-9.119**	0.007	
	(0.0018)	(4.188)	(0.020)	

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