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Keskusteluaiheita – Discussion papers

No. 923

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OPACITY OF YOUNG FIRMS:

FAITH OR FACT?

Hyytinen and Pajarinen gratefully acknowledge the financial support provided by the Finnish Ministry of Trade and Industry. We also thank Alpo Kuparinen, Matti Pietarinen, Otto Toivanen and Pertti Valtonen for helpful discussions and Suomen Asiakastieto Ltd and Dun and Bradstreet Finland for providing us with the corporate level rating data.
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ISSN 0781-6847 06.08.2004

HYYTINEN, Ari – **PAJARINEN,** Mika, **OPACITY OF YOUNG FIRMS: FAITH OR FACT?** Helsinki: ETLA, Elinkeinoelämän Tutkimuslaitos, The Research Institute of the Finnish Economy, 2004, 24 p. (Keskusteluaiheita, Discussion Papers, ISSN, 0781-6847; No. 923).

ABSTRACT: Using patterns of disagreement between credit rating agencies, Donald P. Morgan (American Economic Review, 2002, Vol. 92, No. 4, pp. 874-888) shows that financial institutions are more opaque than other types of firms. In this paper we employ this novel measure to study the determinants of 'opacity' of small and medium sized enterprises (SMEs). We explore them, because a conventional wisdom in the contemporary corporate finance literature postulates that financial constraints are especially acute for younger firms due to their informational opacity. The patterns of disagreement in a large Finnish firm-level panel dataset allow us to render this article of faith to that of fact: The disagreements are inversely related to the age of firms, suggesting that younger SMEs are indeed more 'opaque' than older firms. We can also to an extent replicate Morgan's finding: Two local credit information companies split more often over SMEs from the financial services sector than over other firms. The data also support the idea that the probability of disagreement is highest for those firms who have an intermediate rating, because they are, almost by definition, those whose quality is most difficult to evaluate.

JEL: G14, G31, G32.

KEYWORDS: opacity, small business finance, financial constraints.

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TIIVISTELMÄ: Luottoluokitusyhtiöt arvioivat yrityksien luottokelposuutta. Koska joidenkin yritysten luottokelpoisuutta on vaikeampia arvioida kuin toisten, saattaa (samaa yritystä arvioitaessa) luottokelpoisuusluokituksissa olla eroja eri luottoluokitusyhtiöiden välillä. Käyttämällä näitä eroja Donald P. Morgan (American Economic Review, 2002, Vol. 92, No. 4, s. 874-888) on osoittanut, että rahoituslaitosten luottokelpoisuus on vaikeammin arvioitavissa muihin yrityksiin verrattuna. Tässä tutkimuksessa sovelletaan tätä luottoluokitusten eroihin perustuvaa mittaria suomalaisten pienten ja keskisuurten (pk-) yritysten ”läpinäkymättömyyden” analysoinnissa. Tutkimme pk-yritysten läpinäkymättömyyttä, koska yritysrahoituskirjallisuudessa on vallalla käsitys, että rahoitusrajoitteet koskevat etenkin nuoria pk-yrityksiä. Syynä tähän todetaan usein olevan se, että nuorista pk-yrityksistä on tyypillisesti saatavilla vain vähän tietoa, joka auttaa luottokelpoisuuden selvittämisessä. Tutkimuksemme vahvistaa tätä näkemystä, sillä voimme osoittaa, että luokitusyhtiöiden erimielisyys luottoluokituksesta on sitä harvinaisempaa, mitä pidempään yritys on toiminut. Tutkimuksessa saadaan myös samankaltainen tulos kuin Morgan on saanut yhdysvaltalaisella aineistolla: luottoluokittajien näkemykset eroavat rahoitussektorin yritysten kohdalla muita useammin. Lisäksi poikkileikkausanalyysin tulokset antavat vahvistusta ajatukselle, että luottoluokittelijoiden erimielisyys on todennäköisintä ”keskitason” luokitusten omaavien yritysten keskuudessa, koska niiden todellisen luottokelpoisuuden arviointi on (lähes määritelmän mukaan) vaikeinta.

JEL-luokittelu: G14, G31, G32.

AVAINSANAT: yritysrahoitus, pk-yritykset, rahoitusrajoitteet.

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1 Introduction

A conventional wisdom in the contemporary corporate finance literature says that financial constraints are especially acute for young firms. The intuitive reasoning underlying the wisdom is that recent entrants suffer disproportionately from the constraints because they are informationally opaque. Yet for all its significance, the opacity of young firms is more a piece of faith than that of fact. The aim of this paper is to confront the piece of faith with data. To this end, we measure firm opacity using data on disagreements ('rating splits') between credit information companies and study its determinants.[1]

We borrow this novel measure of opacity from Morgan (2002), in which it is elegantly used to provide evidence on the relative opacity of banks. Using U.S. data of bond ratings and patterns of disagreement between *Moody's* and *Standard and Poor's* credit rating agencies, he shows that financial institutions are more opaque than other types of firms. We apply the new measure to a new data set, Finnish firm-level panel data. The rationale for studying the determinants of the rating splits using this data is as simple as it can get: If a small business is opaque and outsiders cannot easily determine its quality, credit information companies should disagree more often over the creditworthiness of that particular firm than over that of less opaque firms.

We report a number of preliminary findings, which validate our rating and disagreement measures, and one main finding: We first show that there is an unambiguous (unconditional) direct relation between the ratings of firms and the costs of financing: The worse the rating, the higher the costs of financing. We also find that the disagreement measure works in our data like it works in Morgan (2002). Our replication of his analysis with the Finnish firm-level data shows that two (locally known) credit information companies split more often over small businesses from the financial services sector. This replication is, however, only partial, because of lack of fully comparable data. We therefore also test the idea that in a cross-section of firms, the probability of disagreement is highest for those

[1] One could say that it is about time to do so, for there is much less empirical evidence on the *origins* of financial constraints than on their effects. The constraints have for example been found to reduce entry (e.g., Evans and Jovanovic 1989), hamper subsequent investment and growth (Hubbard 1998), result in a type of cash hoarding (Almeida, Campello, Weisbach 2003), and decrease firm survival (Cabral and Mata 2003).

firms who have an intermediate rating, because they are, almost by definition, those whose quality is difficult to evaluate (see, Calem and Stutzer 1995 and Boot, Milbourn and Schmeits 2003). The data support the idea. Taken together, these patterns of the Finnish firm-level rating data enhance our confidence in the quality of the ratings and, especially, in Morgan's disagreement measure.

Our main result is that once unobserved firm-effects are controlled for, the disagreements are inversely related to the age of firms. This negative relation suggests that younger firms are indeed more 'opaque' than established firms and that the conventional wisdom of why young firms suffer from financial constraints can be given a status of fact. An interpretation of the finding is that it reflects a type of reputation acquisition in capital markets, such as modeled in Diamond (1989).

The rest of the paper is organized as follows: In the next section we outline a theoretical framework for our empirical analysis. In section 3 we discuss the data and estimation issues. In section 4 we present the results of our empirical analysis. Section 5 contains a brief summary.

2 Theoretical preliminaries

2.1 Financial constraints and the opacity of small businesses

The mechanisms through which the opacity of infant firms translates into financial constraints are relatively well understood. Diamond (1989) provides a nice analysis of one such mechanism: In his model, the joint influence of adverse selection and moral hazard reduces the ability of an infant firm to raise external finance. These problems are most severe when the firm is young and has only a short track record, because then a severe enough adverse selection (leading to high interest rates) undermines the firm's incentives to behave diligently (i.e. to choose a low risk investment project). If the firm survives to next period despite its risky investment decision, adverse selection is less of a problem, for those that survive are, on average, of better quality. Once adverse selection is less of a problem, the interest rates that financiers demand will be lower. This increases the firm's incentive to choose a less risky project, for it has now more to loose, if the project fails. The implication of this dynamic evolution of incentives is that reputation that is built over time enhances firm's incentives to behave diligently and avoid moral hazard.

There also are other theoretical explanations for why the opacity of smaller or younger firms leads to financial constraints. The opacity of these firms is, however, often taken almost for granted, perhaps because the intuition of the origins of the opacity is familiar to many. Berger and Udell (1998, pp. 616) summarize the origins nicely:

> "Perhaps the most important characteristic defining small business finance is informational opacity. Unlike large firms, small firms do not enter into contracts that are publicly visible or widely reported in the press - contracts with their labor force, their suppliers, and their customers are generally kept private. In addition, small businesses do not issue traded securities that are continuously priced in public markets and (in the US) are not registered with the Securities and Exchange Commission (SEC). Moreover, many of the smallest firms do not have audited financial statements that can be shared with any provider of outside finance. As a result, small firms often cannot credibly convey their quality. Moreover, small firms may have difficulty building reputations to signal high quality or nonexploitive behavior to overcome informational opacity."

While the citation makes a specific reference to the US, these origins are universal and easy to accept. The difficulty in getting empirically a grip of the concept is what in the contemporary literature motivates the use of various proxies, such as firm age and size. A more direct measure is, however, available.

2.2 Disagreement over creditworthiness

As mentioned, we use data on 'rating splits' between credit information companies to study firm opacity.[2] Morgan develops a specific model of rating process that formalizes the rationale for measuring opacity using the splits: Increased uncertainty over the default risk of a firm increases both the risk of overrating and underrating and thus the probability of disagreement. Thus, if there is a lot of uncertainty over the default risk of a firm (i.e., it is opaque), credit information companies should disagree more often over the creditworthiness of the particular firm than over that of the other firms. Morgan also shows that the splits are not sym-

[2] See also Bomberger (1996).

metric (but 'lopsided') if one of the rating firms is more conservative than the other.

While the intuition underlying the splits is clear-cut, it can be sharpened still: The rationale of splits as a measure of opacity emerges also from a standard credit market model with imperfect ex ante screening and hidden types (for this class of models, see Broecker 1990, Thakor 1996, Shaffer 1998, and Hauswald and Marquez 2003). We sketch a formalization of the rationale as follows: There are N firms. Each firm is a potential borrower and has an investment project (that requires a loan from a financial institution). The project of a firm generates a privately appropriable terminal cash flow with probability $p(t)$ and zero with probability $1\text{-}p(t)$, where $t \in \{G, B\}$ denotes the firm's type. The success probability for a firm with a good project ($t = G$) is higher than the corresponding probability of a firm with a bad project ($t = B$). The difference is assumed to mean that the former are creditworthy while the latter are not. Only the firms know the type of the project to which they have access, but it is common knowledge that the probability that a firm's project is good is λ.

Besides the firms, there are two 'credit information companies' that have an access to an ex ante screening technology. The screening technology is uniform across the credit information companies and produces a noisy binary signal that can be either G_s (the firm is tested to be creditworthy) or B_s (the firm is tested to be not creditworthy). As e.g. in Hauswald and Marquez (2003), the technology is characterized for simplicity by the following: $Pr(B_s \mid \text{project is bad}) = Pr(G_s \mid \text{project is good}) = q$, where $q \in [1/2, 1)$. If $q = ½$, the testing technology is completely uninformative since the fraction of creditworthy borrowers among the screened ones is equal to λ.[3] A specific feature of the screening technology is that the higher q, the better its predictive accuracy.

If the signals are conditionally independent (as is usually assumed, see Broecker 1990, Thakor 1996, Shaffer 1998, and Hauswald and Marquez 2003), the probability of a disagreement (i.e., that two signals are different) can be easily computed: $Pr(\text{SPLIT}) = Pr(G_sB_s \mid \text{project is good}) + Pr(B_sG_s \mid \text{project is good}) + Pr(G_sB_s \mid \text{project is bad}) + Pr(B_sG_s \mid \text{project is bad})$, where G_sB_s (B_sG_s) means that

[3] The probabilities that a B-type and G-type pass the test of a representative bank are $(1–q)$ and q, respectively.

the first signal is good (bad) and the second bad (good). By Bayes' rule, $Pr(\text{SPLIT}) = N[2q(1\text{-}q)\lambda + 2q(1\text{-}q)(1\text{-}\lambda)]/N = 2q(1\text{-}q)$. Because $q \geq ½$, this expression shows that $Pr(\text{SPLIT})$ is decreasing in q. This property implies that if a firm belongs to a group of firms with low q (i.e., if it is opaque), credit information companies disagree more often over the creditworthiness of the particular firm than over that of otherwise similar firms. We thus have that observable splits reflect unobservable opacity.

3 Data and variable definitions

3.1 Data sources

We explore the disagreements using a panel data of 4021 small and medium-sized enterprises (SMEs). Our data cover the years from 1999 to 2002 and come from two local credit information companies that dominate the industry providing credit risk information about SMEs in Finland.[4] The data are randomly drawn (for 1999) from the database of *Asiakastieto Ltd,* which maintains a comprehensive database of Finnish firms.[5] An important source of these data is the trade register of The National Board of Patents and Registration of Finland. The register is a public data bank on business information that contains, for example, the existence of a certain company, its articles of association, its representatives and submission of the latest annual accounts.[6] Besides these business information data, *Asiakastieto's* database includes data on payment and default history (gathered from a variety of sources) and other business information, collected for example from the financial press. Importantly for us, the database also includes a letter credit rating, called Rating Alfa, generated by the company and its credit analysts. We match

[4] While the industry is next to a duopoly, some other firms also provide corporate data and a limited range of credit risk evaluation services. The most prominent of such firms is *Balance Consulting Ltd*. This firm does not, however, offer a rating product that is comparable with those we use in this paper.

[5] *Asiakastieto* offers credit information services to support credit granting, client selection and other related financial decision-making. The major Finnish deposit banks mainly own Asiakastieto. The company was established in 1963 and in 2002 its turnover amounted to nearly to 16 million euros. For more information, see http://www.asiakastieto.fi/en/asiakastieto/koti.htm.

[6] In general, new businesses are required by Finnish legislation be notified for entry in the trade register. Some businesses that have no obligations to register themselves nevertheless do so, because being in this public register may enhance trust towards trade partners and because registration also protects the name of the registered firm. It has been estimated that about one hundred new businesses are entered in the trade register on an average day.

these data to a corresponding rating of *Dun and Bradstreet Finland Ltd*., called D&B Rating.[7] Finally, we match to these data to some elementary patent information from the European Patent Office (EPO).

3.2 Disagreements data

The letter ratings of both *Asiakastieto* and *Dun and Bradstreet Finland* resemble to a certain extent those of the major bond-rating agencies, such as *Moody's* and *Standard and Poor's*. Like that of the major agencies, the objective of both companies' rating is to provide a forward-looking measure of a potential borrower's creditworthiness. An initial rating is given when the firm appears for the first time in the trade register of The National Board of Patents and Registration of Finland. The rating is reviewed if new information that becomes available warrants a change. The ratings are thus an outcome of the process of assigning an estimate for the borrower's future loan performance based on the information that is available about the borrower at each point in time. What's more, the ratings of both firms follow the well-known taxonomy of creditworthiness: As we will explain in more detail below, there are separate classes of ratings for firms that are "creditworthy", "borderline cases" and "not creditworthy". These ratings are, however, firm specific. This is to be contrasted with the ratings of the major bond-rating agencies, which are bond or issue specific.

The two companies use both personal data of small-business owners and directors, as well as a variety of firm-specific data to determine the rating. The firm-specific data include but is not limited to financial statements and payment and credit history information. This type of data is widely used to predict creditworthiness. Both firms also collect data on businesses' payment performance directly from creditors. Recent research has documented that sharing of this type of payment history information helps to predict failure (Kallberg and Udell 2003).

Even if the letter ratings of *Asiakastieto* and *Dun and Bradstreet Finland* share many features of those of the major bond-rating agencies, there is quite obviously a difference in the quality of the process that generates the ratings. The

[7] During the period of our data, *Dun and Bradstreet Finland Ltd* was a part of the worldwide *Dun & Bradstreet Corporation.* In October 2003, Bonnier Affärsinformation Holding AB announced that it would buy the Nordic operations of *Dun & Bradstreet Corporation*. For more information, see http://www.dnb.fi/index.htm and http://www.dnb.com/us/.

analysis underlying *Asiakastieto's* and *Dun and Bradstreet Finland's* ratings is understandably more restrictive in scope than that underlying the major agencies' ratings. A likely consequence of the more restricted scope is that the forward-looking measures of the two local credit information companies are noisier predictors of creditworthiness than those of the major agencies. Another consequence is that the range of the letter ratings cannot be as fine-tuned as that of the major agencies, which have up to 16 categories (Morgan 2002): The rating of *Asiakastieto* has seven categories and ranges from C (the worst credit) to AAA (the best credit). Once we exclude a specific rating for new firms and an explicit category for firms with missing ratings (see below), the rating of *Dun and Bradstreet Finland* has five categories and ranges similarly from C (the worst credit) to AAA (the best credit). The difference in the number of categories arises, because the credit information companies have a slightly different division of sub-categories of the better credits (i.e., from A to AAA).

Even if the ratings available to us are not identical to the ratings of the major rating agencies, we have other motivations to use this type of credit risk measurement data when studying the opacity of SMEs. The first reason is that the process leading to the ratings available to us is not dramatically different from "credit scoring" by lenders, in which a single quantitative measure (score) is typically assigned to a potential borrower to indicate her creditworthiness (Frame, Srinivasan and Woosley 2001). Second, the process is also in many ways similar to banks internal credit rating of borrowers (Elsas and Krahnen 1998, and Machauer and Weber 1998), to which expert analysis and data-collection are factors of input.[8] Our ratings represent, in some sense, a kind of hybrid that emerges from these accounting based credit-scoring and expert systems, which are the two traditionally most-used types of credit risk measurement (Altman and Saunders 1998).

We measure the ratings at the end of each year from 1999 to 2002 for each firm in our sample.[9] Both firms follow the familiar taxonomy, for they argue that

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[8] Credit scores have traditionally been used in determining the creditworthiness of consumers. For an analysis of the role of credit scoring in small business finance, see Frame, Srinivasan and Woosley (2001).

[9] This method of measurement means that we essentially ignore credit rating migration. Migration typically refers to changes in the rating of a company's public debt and it can have subtle implications for credit pricing and credit risk measurement (Altman 1998, Löffler 2004). Migration arises, because bond ratings are usually first assigned to the public debt at the time of issuance and then

firms with A ratings (or better) are "creditworthy", with B ratings "borderline cases" and with C ratings "not creditworthy". Following Morgan (2002), we calibrate these letter ratings to a single numeric scale, in which better letter ratings correspond to lower numbers: AAA = AAA = 1, …, C = C =5. We also create a sixth category for missing ratings (Missing = 6). A missing rating in a given year mirrors a type of opacity because it means that there was not enough information available about the firm then. Missing ratings in our data reflect lack of information (and not selection), because both credit information companies pursue to evaluate *all* active Finnish firms, incorporated or not, which are in a business to generate turnover.[10] A difference between *Asiakastieto* and *Dun and Bradstreet Finland* is, however, that the latter has an explicit category for firms suffering from this type of opacity, whereas in *Asiakastieto's* data we simply observe a missing rating. In the empirics, we keep the firms with missing ratings in the analysis, but do not assume that a missing rating implies a stance on the creditworthiness of a firm like the letter ratings do.

4 Empirical analysis

4.1 Preliminary analysis

The aim of this preliminary analysis is to validate the rating data as well as the splits of ratings as a measure of opacity. We do it (i) by showing that there is there is an intuitive (unconditional) direct relation between the ratings of firms and the costs of financing, (ii) by documenting that the disagreement measure works in our data in the same way it works in Morgan's (2002) data and (iii) by demon-

re-evaluated periodically. As we explained, the two local Finnish credit information companies assign an initial letter rating to a firm as soon as it appears in the trade register of The National Board of Patents and Registration of Finland. The credit information companies monitor the creditworthiness of the firm over time and make changes to its rating when deemed necessary. This ongoing monitoring is, however, more passive and mechanic than the reviews of the major credit rating agencies. We leave it for future work to better account for the migration that these reviews give a rise to in the SME ratings data.

[10] This detail is important for two reasons: First, if the rated firms request for ratings, a selection bias might arise (see Cantor and Packer, 1997). Second, the database of neither Finnish credit information company is a result of a credit inquiry by one of their customers (potential lenders). This characteristic means that unlike for example *Dun and Bradstreet's* corporate data in the U.S. (see, Kallberg and Udell 2003), our sample is independent of revealed (potential) demand for credit.

strating that in a cross-section, the probability of disagreement is highest for those firms who have an intermediate rating. This non-linearity in the creditworthiness should arise, because the firms that are difficult to evaluate are neither of very high quality nor of very low quality. These borderline cases therefore receive, almost by definition, an intermediate rating (see also Calem and Stutzer 1995, pp. 194).[11]

Figure 1 shows that there indeed is an intuitive (unconditional) direct relation between the ratings of firms and the costs of financing: The worse the rating, the higher the costs of financing. The median ratio of financing costs to total assets is well below 1% for firms with a very good rating, but as high as 3% for firms with the worst rating. The difference in the costs of financing is clearly non-negligible. The direct relation can be observed also if we use means instead of medians. As the figure shows, the relation also is also robust to using different scaling variables.

[INSERT FIGURE 1 HERE]

Unfortunately, we cannot fully replicate Morgan's analysis with our data, because *Dun and Bradstreet Finland* does *not* evaluate at all traditional deposit banks or insurance companies. The reason for this is that such firms do not in the course of their ordinary business generate "turnover" from sales in the traditional sense. This lack of data means that we are forced to exclude these types of firms from the analysis and that our definition of the financial services sector is clearly different from that of Morgan (2002). Our financial services sector consists of (small) investment banks, leasing firms, financial advisory firms, financing companies and the like. While these financial firms are not suspect to bank runs or contagion like deposit banks are, they are in the business of providing savings instruments, credit, liquidity and trading, which are the primary sources of opacity

[11] A non-linearity of this type is also implied by the model of Boot, Milbourn and Schmeits (2003), where credit ratings serve as a coordinating mechanism in an environment in which multiple equilibria can obtain. The model shows that multiple equilibria are possible *only* for firms of medium quality, because the risk-taking of these firms is, in equilibrium, contingent on what is anticipated in the capital markets The model also predicts that the likelihood of being put on a credit watch procedure (as opposed to being directly down- or upgraded by a credit rating agency) is larger for firms of medium quality than for firms of low or high quality.

for deposit banks. We therefore believe that they can be used to explore whether the disagreement measure works in our data in the same way it works in Morgan's (2002) data.

Table 1 reports various measures of disagreement conditional on 24 industry dummies, level of credit rating and firm age. The measures are average rating, correlation between the two ratings, Kappa statistic, average absolute gap and rating gap distribution. We find that three patterns characterize the data: First, almost all of these measures suggest that the two credit information companies disagree more often over the creditworthiness of small businesses from the financial services sector than over that of other small businesses. Both the coefficient of correlation and the Kappa statistic obtain, for example, the lowest value for financial firms, whereas the average absolute gap is the highest for them. Second, the table also provides some support for the view that disagreements are more common among firms with an intermediate credit rating. Compared to firms with A or C-rating, the firms with an intermediate credit rating have the highest average absolute gap. Finally, there is more often disagreement over the creditworthiness of younger firms.

The first of the above patterns is also present in Morgan's (2002) data, which suggest that our split ratings are not dramatically different from those computed on the basis of the major rating agencies.[12] The second and third findings are new observations, but consistent with our expectations.

[INSERT TABLE 1 HERE]

Table 2 reports the average number of split ratings, denoted SPLIT, across different sub-samples, where SPLIT = 1 if *Asiakastieto's* rating ≠ *Dun and Bradstreet Finland's* rating and zero otherwise. The conditioning variables are the same as those in Table 1, except for the industry dummies which we no longer display in detail. The means and *t*-tests verify that SPLITs are more common among the firms from the financial sector, younger firms and firms with an intermediate credit rating.

[12] The left-most column shows that the ratings are asymmetric (i.e., "lopsided"), with one credit information company lower than the other. This is consistent with Morgan (2002), but reflects to some extent that fact that missing ratings obtains the highest score and that *Dun and Bradstreet Finland* has more of them.

[INSERT TABLE 2 HERE]

Is the finding that there is more often disagreement over the creditworthiness of firms with an intermediate credit rating than over other firms statistically significant? To address the question, we therefore report in Table 3 three regressions to illustrate that it is: In the first two columns, the dependent variable is SPLIT and the method of estimation is, respectively, OLS and Logit. In the third column, the dependent variable is the absolute gap, GAP, (i.e. 0, 1, 2, 3+) and the method of estimation is ordered Probit. The explanatory variables are in the all three columns in the form of a spline: D_ABC = 1 if a firm has no missing rating observations and zero otherwise; D_BC = 1 if the rating is B or C and D_C = 1 the rating is C; the omitted category is that of firms with missing ratings.[13] The use of this specification is convenient, for should we find that the coefficient of D_BC is positive and the coefficient of D_C is negative, it would suggest that there is more often disagreement over the creditworthiness of firms with an intermediate credit rating than over other firms.[14]

Table 3 shows that the coefficient of D_BC is positive and the coefficient of D_C is negative. The finding is in line with our expectation and echoes the univariate results. In Table 4, we re-estimate the models of Table 3 after adding a vector of industry dummies. The omitted category is that of firms from the financial services sector. These estimations echo our earlier findings, too: First, controlling for the industry, disagreements are more common among firms with an intermediate credit rating. Second, controlling for the level of rating, the credit information companies disagree more often over the creditworthiness of small businesses from the financial services sector than over that of other small businesses. The coefficients of the industry dummies show that the only industry that apparently does not differ from the financial services sector is the energy sector.

[13] Year-effects (coefficients not reported) are also included.

[14] To see this, note that the coefficient of D_ABC reflects the effect of having an A-rating on SPLIT relatively to (sometimes) having none. The coefficient of D_BC shows, in contrast, the effect of a decrease in rating from A to B. Finally, the coefficient of D_C reflects the effect of a decrease in rating from B to C.

[INSERT TABLE 3 HERE]

[INSERT TABLE 4 HERE]

So far we have not allowed for firm heterogeneity or for permanent differences across firms (i.e., fixed firm-specific effects). This reflects a deliberate choice, for if we had exploited fully the panel nature of our data and controlled for fixed firm-specific effects, cross-sectional differences could not have been uncovered. For example, the difference between firms from the financial services industry firms and other firms would have gone unnoticed. We have therefore not used in this preliminary analysis empirical models that sweep such differences by design out.

4.2 Main analysis

The conventional wisdom in the contemporary corporate finance literature postulates that financial constraints are especially acute for younger firms because they are informationally opaque. In terms of our simple model, the wisdom suggests that the accuracy of the screening technology is an increasing function of firm age, i.e. that $q = q(AGE; X)$ with $dq(AGE; X)/d(AGE) \equiv q'(AGE) > 0$, where AGE denotes the age and X the determinants of q other than AGE. Because *Pr*(SPLIT) is decreasing in q, we can test the conventional wisdom by exploring whether the splits are negatively related to AGE. The simple model suggests, in addition, that because q is a function of X, testing for the conventional wisdom requires that observed and unobserved heterogeneity across SMEs is controlled for. [15] We do not want the coefficient of AGE to reflect them.

To test the conventional wisdom, we consider the following set of regression models:

Model 1: We regress SPLIT on D_ABC, D_BC and D_C and the year-effects, as we did in Table 3, but include also AGE, and its square (AGE2) in the specification. We allow for the non-linear effect, because the effect of AGE on

[15] The findings of Penning and Garcia (2004) echo the importance of this type unobserved heterogeneity across SMEs, as they find that the roots of the heterogeneity in the usage of hedging instruments among SMEs originate in part from firm-specific differences in attitudes, perceptions and ownership structure.

SPLIT may weaken as the firm matures. We also allow for fixed effects that control for unobserved firm heterogeneity.

Model 2: To better control for observable, time-varying firm heterogeneity, we add a number of new regressors to Model 1. The vector of new explanatory variables consists of the following: SALES = turnover of the firm in million of euros, ROA = return on assets, DEFAULT = number of unsettled debt payments, PATENT_EC = number of patents registered via European Patent Office, DEBT = ratio of liabilities to total assets, D_DEBT = 1 if DEBT > 1, GR_SALES = percentage sales growth last period, AUDITOR = 1 if the firm has an authorized auditor (as specified in the Finnish law), AUDIT = 1 if the firm's auditor has issued an auditing note before approving of the firm's financial statements, and INSOLVENT = 1 if the firm is in an on-going bankruptcy or reorganization procedure.[16] Because all these additional explanatory variables are time-varying, we can still include fixed effects.

Model 3: We drop the fixed effects but add a number of time-invariant explanatory variables into Model 2. They include EXPORTER = 1 if the firm has exports, dummies for the organizational form (COMP_FORM1 = 1 if the firm is a limited partnership, COMP_FORM2 = 1 if the firm is a cooperative, COMP_FORM3 = 1 if the firm is a limited liability company; omitted category is an unlimited partnership), dummies for the type of the owner (OWNER1 = 1 if the firm is owned by state or municipality and OWNER2 = 1 if the firm is foreign-owned; omitted category is those owned by domestic private owners); 24 dummies for the industry (INDUSTRY) and, finally, 20 dummies for the geographic location of the firms (REGION).

To begin with, we treat these models as linear probability models. We estimate Models 1 and 2 using the standard least-squares dummy variable (LSDV) estimator, which allows for firm fixed effects.[17] We also estimate Model 3 as a

[16] We have winsorized ROA and GR_SALES to limit the effects of outliers. Our results are, however, robust to not winsorizing the data in this way. We have also truncated DEBT at 1, if the ratio of liabilities to total assets exceeded one. D_DEBT identifies such firms.

[17] The random effects Probit model in spirit of Butler and Moffit (1982) is an alternative approach. The approach specifies that the error term of the model is a composition of (i) a normally distributed error with mean zero that is independent across periods and firms and of (ii) a firm-specific term. The firm-specific term should be uncorrelated with the included explanatory variables in all periods independent across firms and time invariant. While this approach allows for time invariant regressors, the restrictions on the error term are difficult to satisfy in practice. See Greene (2003) for other approaches.

standard linear probability model without fixed effects (i.e., using OLS).[18] The results are displayed in Table 5, Panel A. They show that the coefficient of AGE is negative and statistically significant. This negative relation suggests that younger firms are indeed more ‘opaque’ than established firms and that the conventional wisdom of why young firms suffer from financial constraints can be given a status of fact. A more nuanced interpretation of the finding is that the relation reflects a type of reputation acquisition in capital markets, such as modeled in Diamond (1989).

[INSERT TABLE 5 HERE]

Linear probability model has known weaknesses. In Panel B of Table 5 we therefore report estimation results that take into account that SPLIT is a binary variable: The first two columns of Panel B report the conditional fixed-effect Logit (Chamberlain 1980) estimations of the first two models of Panel A. The number of observations in the estimating sample drops, because the estimator utilizes the panel dimension of our data and abandons firms for which SPLIT does not vary over time. In the third column estimate the model as a standard Logit model using the full sample and the explanatory variables from the third column of Panel A (with no fixed effects). The results of Panel B confirm our earlier finding: younger firms are indeed more ‘opaque’ than established firms.

With fixed effects, the variation in the dependent variable that remains to be explained originates from within-firm variation in SPLIT. The effect of AGE thus captures what we expected: The older a firm becomes, the less likely that the two credit information companies disagree over its creditworthiness. The fixed effects estimations also show the coefficient of DEFAULT is negative. This finding suggests that if a firm defaults its payment, disagreement over its creditworthiness reduces. The fixed effects estimations also provide some evidence that being able to raise debt from the market is negatively associated with opacity and that having an authorized auditor has a similar effect. Finally, it is of interest to note that that neither patenting nor sales growth have an effect in SPLIT. There are many poten-

[18] There is no point in estimating this specification using the estimators that allow for fixed effects. The reason for this is that the additional explanatory variables in this specification are time-invariant and thus effectively dropped when the fixed effects are present.

tial explanations for lack of an effect, but one of them is these variables explain only poorly temporal variation in SPLIT.

4.3 Robustness analysis

In the following, we consider and try to rule out alternative explanations for our empirical findings. Taking the robustness tests each in turn:

Robustness test 1 (additional covariates): Morgan (2002) argues that the nature of a firm’s assets is an important determinant of its opacity. To account for this possibility and to check whether omitted variables of this type drive our main finding, we add ratios of intangibles, tangibles, inventories, receivables and cash to total assets to the models reported in the two panels of Table 5. We do not report these re-estimations in detail, but just note that they echo our earlier findings. In particular, the coefficient of AGE is negative and significant in all these estimations at better than the 5% level. The Wald-tests for the joint significance of the asset variables are *not* significant in the models with fixed effects. Interestingly, they are jointly significant in the OLS (p-value = 0.0065) and Logit (p-value = 0.0026) estimations, where the fixed effects are not controlled.

Robustness test 2 (size versus age): Our interpretation of the received corporate finance literature is that when it comes to opacity, firm age matters more than firm size. Others may find this view unconvincing, because the two are positively correlated and because firm size may disproportionately alleviate opacity. Size may matter more than age, because larger firms interact with their environment more often than small firms do. For example, they may be forced to actively trade and contract with other firms, consumers and investors because of scale reasons. To test whether our main finding is robust to using an alternative, possibly better measure of firm size or non-linearities in the relation between firm size and opacity, we re-run the fixed effects regressions of Table 4 as follows: First we replace SALES with ASSETS, defined as the total assets of a firm. Second, we replace SALES with EMP, defined as the number of employees of the firm. Third, we include the second and third order polynomials of SALES to account for the possible non-linearity. We do not report the results of these estimations in detail, but note only that our main result does not change: The coefficient of AGE remains negative and statistically significant in all these new regressions, too.

5 Conclusions

A conventional wisdom in the contemporary corporate finance literature says that financial constraints are especially acute for younger firms. The intuitive reasoning underlying the wisdom is that recent entrants suffer disproportionately from the constraints because they are informationally opaque. Yet for all its significance, the opacity of younger firms is more a piece of faith than of fact. The aim of this paper is to study the determinants of firm opacity and, especially, to confront the piece of faith with data.

To study the determinants of firm opacity, we borrow a novel measure of opacity from Morgan (2002): data on disagreements (‘rating splits’) between credit information companies. We then study the determinants of these rating splits using Finnish firm-level panel data.

We find that there is an intuitive unconditional direct relation between the ratings of firms and the costs of financing: The worse the rating, the higher the costs of financing. The median ratio of financing costs to total assets is well below 1% for firms with a very good rating, but as high as 3% for firms with the worst rating. The disagreement measure works in our data like it works in Morgan (2002): Our replication with the Finnish firm-level data suggests that two (locally known) credit information companies split more often over small businesses from the financial services sector. We also find that the probability of disagreement is highest for those firms who have an intermediate rating. The reason for this is that they are, almost by definition, those whose quality is difficult to evaluate. These findings validate rating data and, especially, the usefulness of the disagreement measure as a proxy for opacity in SME data.

Our main result is that once unobserved firm-effects are controlled for, the disagreements are inversely related to the age of firms. This negative relation suggests that younger firms are indeed more ‘opaque’ than established firms and that the conventional wisdom of why young firms suffer from financial constraints can be given a status of fact. A more nuanced interpretation of the finding is that it reflects a type of reputation acquisition in capital markets, such as modeled in Diamond (1989).

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Table 1. Measures of rating differences

	Average ratings: (AsTie/ D&B)	Correl-ation between ratings	Kappa stat.	Average absolute gap	Rating gap distribution		
					Gap = 1	Gap = 2	Gap = 3+
Panel A:							
Sample total	2.5/2.7	0.55	0.27	0.73	0.42	0.06	0.06
Panel B:							
Financial firms (65-67)	2.4/4.3	0.33	0.03	2.16	0.24	0.13	0.46
Other firms	2.5/2.7	0.56	0.27	0.72	0.42	0.06	0.05
IND1 (01-14)	2.5/2.6	0.64	0.34	0.63	0.36	0.09	0.02
IND2 (15-16)	2.7/2.9	0.70	0.31	0.55	0.43	0.04	0.01
IND3 (17-19)	2.6/2.9	0.68	0.30	0.69	0.41	0.07	0.05
IND4 (20-21)	2.5/2.8	0.66	0.28	0.68	0.45	0.06	0.03
IND5 (22)	2.6/2.7	0.41	0.24	0.82	0.42	0.08	0.07
IND6 (23-25)	2.4/2.6	0.62	0.26	0.65	0.48	0.02	0.04
IND7 (27-28)	2.2/2.3	0.63	0.32	0.63	0.41	0.06	0.03
IND8 (29,34-35)	2.4/2.5	0.64	0.27	0.67	0.46	0.05	0.03
IND9 (30-33)	2.4/2.5	0.67	0.31	0.62	0.42	0.06	0.03
IND10 (26,36-37)	2.5/2.7	0.54	0.35	0.62	0.36	0.07	0.03
IND11 (40-41)	2.3/2.9	0.25	0.11	0.79	0.49	0.02	0.07
IND12 (45)	2.5/2.6	0.56	0.25	0.68	0.45	0.06	0.03
IND13 (50)	2.5/2.7	0.58	0.25	0.71	0.43	0.07	0.05
IND14 (51)	2.4/2.7	0.61	0.30	0.67	0.41	0.05	0.04
IND15 (52)	2.5/2.7	0.59	0.31	0.64	0.40	0.05	0.04
IND16 (55)	2.9/3.1	0.64	0.22	0.74	0.47	0.07	0.04
IND17 (60-63)	2.5/2.8	0.59	0.28	0.65	0.42	0.06	0.03
IND19 (70-71)	2.6/3.1	0.40	0.21	0.99	0.37	0.06	0.15
IND20 (64,72-73)	2.4/2.7	0.56	0.23	0.79	0.42	0.07	0.07
IND21 (741)	2.4/2.7	0.45	0.22	0.80	0.42	0.06	0.07
IND22 (742-743)	2.3/2.6	0.46	0.24	0.78	0.43	0.05	0.07
IND23 (744-748)	2.6/2.8	0.55	0.27	0.77	0.41	0.05	0.08
IND24 (75-98)	2.5/2.8	0.54	0.25	0.78	0.42	0.05	0.07
Panel C:							
Rating	2.5/2.5	0.65	0.29	0.57	0.45	0.06	0.00
A-rating	2.2/2.2	0.47	0.31	0.49	0.41	0.04	0.00
B-rating	3.4/4.0	-0.68	-0.24	1.07	0.62	0.20	0.02
C-rating	4.3/4.9	-0.50	-0.22	0.79	0.79	0.00	0.00
Missing rating	3.1/5.9	-0.51	-0.07	3.05	0.03	0.09	0.82
Panel D:							
Young firms	2.7/2.9	0.53	0.24	0.78	0.43	0.06	0.07
Old firms	2.3/2.6	0.57	0.29	0.68	0.41	0.05	0.05

Note: NACE 2002 Industry Codes in parentheses. The data source is Astie = Suomen Asiakastieto Ltd and D&B = Dun and Bradstreet Finland.

Table 2. Prevalence of rating splits

	SPLIT			T-test for means	
	Observations	Mean	S.D.	*t* statistics	*p*-value
Panel A:					
Sample total	12546	0.534	0.499		
Panel B:					
Financial firms	123	0.837	0.371	9.084	0.000
Other firms	12423	0.531	0.499		
Panel C:					
Missing rating	826	0.944	0.229	47.598	0.000
Rating	11720	0.505	0.500		
A-rating	9997	0.450	0.498	-33.046	0.000
B-rating	1176	0.840	0.367	2.546	0.011
C-rating	547	0.788	0.409		
Panel D:					
Young firms	6414	0.557	0.497	5.256	0.000
Old firms	6132	0.510	0.500		

Table 3. Basic regression

	Dependent variable: SPLIT				Dependent variable: GAP	
	(1) OLS		(2) Logit		(3) Ordered Probit	
	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
D_ABC	-0.485	0.017 ***	-3.005	0.153 ***	-3.373	0.058 ***
D_BC	0.390	0.014 ***	1.873	0.082 ***	1.014	0.035 ***
D_C	-0.049	0.024 **	-0.335	0.132 **	-0.434	0.058 ***
YEAR	Yes		Yes		Yes	
Observations	12546		12546		12546	
Wald/LR test	283.09		1702.03		5114.62	
degr. of freedom	6, 12539		6		6	
significance	0.000		0.000		0.000	
Log likelihood	-		-7815.85		-10592.88	
$R^2_{(adj./pseudo)}$	0.12		0.10		0.19	

Table 4. Basic regression with industry dummies

	Dependent variable: SPLIT				Dependent variable: GAP	
	(1) OLS		(2) Logit		(3) Ordered Probit	
	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
D_ABC	-0.473	0.017 ***	-2.951	0.154 ***	-3.343	0.058 ***
D_BC	0.394	0.014 ***	1.894	0.083 ***	1.028	0.035 ***
D_C	-0.049	0.024 **	-0.335	0.132 **	-0.437	0.059 ***
INDUSTRY1	-0.161	0.051 ***	-1.047	0.297 ***	-0.558	0.137 ***
INDUSTRY2	-0.169	0.057 ***	-1.082	0.320 ***	-0.640	0.152 ***
INDUSTRY3	-0.153	0.060 **	-1.020	0.335 ***	-0.564	0.160 ***
INDUSTRY4	-0.133	0.058 **	-0.924	0.326 ***	-0.529	0.155 ***
INDUSTRY5	-0.096	0.051 *	-0.749	0.299 **	-0.356	0.138 **
INDUSTRY6	-0.112	0.060 *	-0.826	0.329 **	-0.524	0.157 ***
INDUSTRY7	-0.119	0.048 **	-0.857	0.288 ***	-0.477	0.131 ***
INDUSTRY8	-0.104	0.049 **	-0.791	0.292 ***	-0.483	0.133 ***
INDUSTRY9	-0.139	0.055 **	-0.951	0.310 ***	-0.541	0.146 ***
INDUSTRY10	-0.173	0.054 ***	-1.099	0.307 ***	-0.587	0.144 ***
INDUSTRY11	-0.056	0.083	-0.581	0.422	-0.383	0.216 *
INDUSTRY12	-0.101	0.045 **	-0.776	0.276 ***	-0.445	0.122 ***
INDUSTRY13	-0.104	0.048 **	-0.791	0.286 ***	-0.436	0.129 ***
INDUSTRY14	-0.137	0.045 ***	-0.941	0.275 ***	-0.552	0.122 ***
INDUSTRY15	-0.151	0.045 ***	-1.003	0.278 ***	-0.582	0.124 ***
INDUSTRY16	-0.124	0.048 **	-0.886	0.289 ***	-0.523	0.130 ***
INDUSTRY17	-0.132	0.046 ***	-0.915	0.281 ***	-0.521	0.126 ***
INDUSTRY19	-0.114	0.047 **	-0.838	0.286 ***	-0.430	0.128 ***
INDUSTRY20	-0.086	0.049 *	-0.711	0.293 **	-0.443	0.134 ***
INDUSTRY21	-0.085	0.046 *	-0.706	0.280 **	-0.402	0.125 ***
INDUSTRY22	-0.082	0.047 *	-0.692	0.282 **	-0.402	0.127 ***
INDUSTRY23	-0.129	0.047 ***	-0.907	0.284 ***	-0.512	0.128 ***
INDUSTRY24	-0.117	0.046 **	-0.847	0.280 ***	-0.471	0.125 ***
YEAR	Yes		Yes		Yes	
Observations	12546		12546		12546	
Wald/LR test	60.00		1744.36		5167.66	
degr. of freedom	29, 12516		29		29	
significance	0.000		0.000		0.000	
Log likelihood	-		-7794.68		-10566.36	
$R^2_{(adj./pseudo)}$	0.12		0.10		0.20	

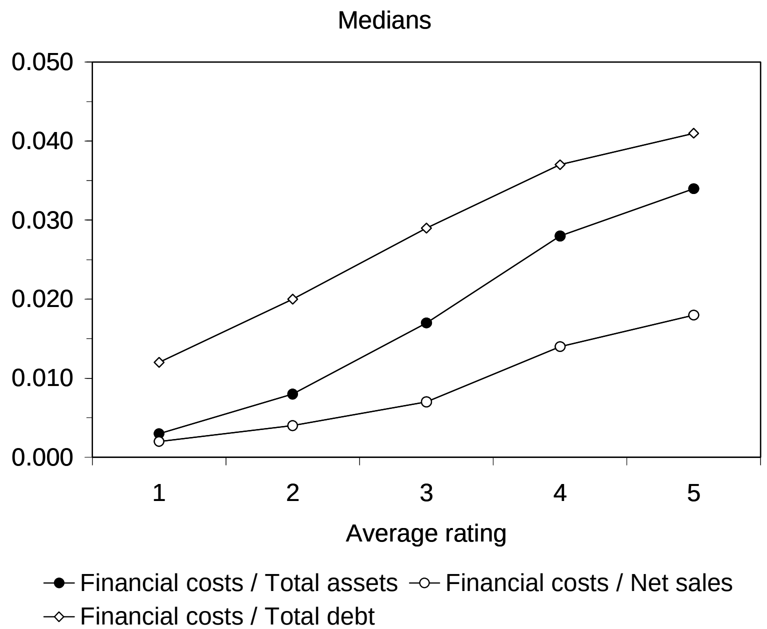
Note: Industry controls are equal to table 1, excluded industry is Financial firms (NACE 65-67).

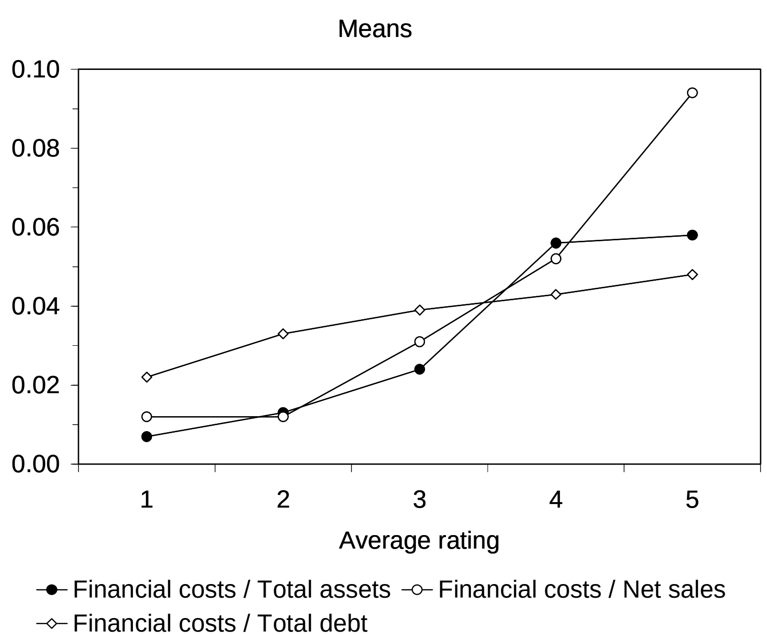
Table 5. Fixed-effects models

	PANEL A: Dependent variable SPLIT								
	FIXED EFFECTS (WITHIN)						OLS		
	(1)			(2)			(3)		
	Coeff.	S.E.		Coeff.	S.E.		Coeff.	S.E.	
D_ABC	-0.494	0.029	***	-0.493	0.029	***	-0.506	0.020	***
D_BC	0.492	0.023	***	0.500	0.023	***	0.473	0.017	***
D_C	0.077	0.039	**	0.107	0.039	***	0.056	0.029	*
AGE	-0.035	0.007	***	-0.039	0.007	***	-0.002	9.60E-04	**
AGE2	2.26E-04	1.85E-04		2.28E-04	1.84E-04		4.35E-05	1.46E-05	***
SALES				9.58E-04	0.003		-0.002	9.27E-04	***
ROA				0.028	0.032		0.100	0.021	***
DEFAULT				-0.086	0.025	***	-0.107	0.014	***
PATENT_EC				0.080	0.077		-0.026	0.015	*
D_DEBT				0.027	0.040		-0.026	0.025	
DEBT				-0.197	0.046	***	-0.198	0.019	***
GR_SALES				-0.009	0.009		-0.008	0.007	
AUDITOR				-0.044	0.022	**	-0.006	0.010	
AUDIT				0.005	0.031		0.004	0.021	
INSOLVENT				-0.015	0.145		-0.015	0.116	
EXPORTER							0.001	0.013	
COMP_FORM1							0.083	0.094	
COMP_FORM2							-0.034	0.109	
COMP_FORM3							-0.024	0.086	
OWNER1							0.066	0.053	
OWNER2							0.004	0.029	
INDUSTRY	No			No			Yes		
REGION	No			No			Yes		
YEAR	Yes			Yes			Yes		
Observations	10969			10969			10969		
Wald test	122.57			53.57			27.67		
degr. of freedom	7, 7154			17, 7144			66, 10902		
significance	0.000			0.000			0.000		
R^2	0.11			0.11			0.14		

	PANEL B: Dependent variable SPLIT					
	CONDITIONAL FIXED-EFFECTS LOGIT				Logit	
	(1)		(2)		(3)	
	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
D_ABC	-3.597	0.320 ***	-3.618	0.329 ***	-3.391	0.203 ***
D_BC	2.588	0.168 ***	2.642	0.170 ***	2.345	0.098 ***
D_C	0.955	0.327 ***	1.505	0.389 ***	0.481	0.180 ***
AGE	-0.164	0.040 ***	-0.192	0.041 ***	-0.009	0.004 **
AGE2	0.002	0.001	0.001	0.001	1.97E-04	6.75E-05 ***
SALES			0.006	0.016	-0.011	0.005 **
ROA			0.185	0.182	0.469	0.099 ***
DEFAULT			-0.829	0.235 ***	-0.862	0.124 ***
PATENT_EC			0.439	0.412	-0.129	0.075 *
D_DEBT			0.338	0.287	-0.257	0.136 *
DEBT			-1.027	0.261 ***	-0.908	0.089 ***
GR_SALES			-0.064	0.051	-0.042	0.035
AUDITOR			-0.247	0.123 **	-0.029	0.047
AUDIT			0.045	0.196	0.013	0.109
INSOLVENT			1.013	1.070	0.565	0.671
EXPORTER					0.003	0.063
COMP_FORM1					0.363	0.451
COMP_FORM2					-0.169	0.525
COMP_FORM3					-0.148	0.417
OWNER1					0.308	0.248
OWNER2					0.014	0.133
INDUSTRY	No		No		Yes	
REGION	No		No		Yes	
YEAR	Yes		Yes		Yes	
Observations	6915		6915		10969	
LR Chi^2	769.65		819.71		1825.68	
degr. of freedom	8		18		66	
significance	0.000		0.000		0.000	
Log likelihood	-2201.56		-2176.53		-6670.24	

Figure 1. Financial costs and rating





Note: Average rating = mean of the ratings of Asiakastieto and Dun & Bradstreet. Rating number is the larger, the worse the creditworthiness of the firm (i.e., 1 indicates the best rating, and 5 the worst).

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