Online Appendix for

"The Costs of Being Private: Evidence from the Loan Market"

Anthony Saunders
Sascha Steffen

This appendix is split into 6 sections. Section 1 provides institutional details, section 2 shows methodological aspects of propensity score estimation, section 3 provides instrumental variable and treatment effects models using additional instruments, section 4 provides a detailed discussion of the different channels that explain the loan cost differences between private and public firms using additional proxies and tests, section 5 analyses various predictors of firm defaults, and section 6 provides further tests related to the differences in future performance of private versus public firms.

1. Institutional Setting

Since only a limited number of papers are concerned with the UK market and differences between private and public companies in particular, we provide further information on UK company law in this section.[1]

In the UK, all public and private limited liability companies are formed by registering with UK Companies House.[2] Public companies must add either "public limited company" or "plc" to their name and must have a minimum share capital of GBP 50,000. Private limited companies, on the other hand, need only include "limited" and they are not required to have a minimum share capital. The most important difference between a private and a public company is the ability of public firms to issue public equity. In this paper, a public company is a firm which is listed on the London Stock Exchange (Section 81 of Companies Act 1985).

The Companies Act of 1967 requires all public and private limited liability companies to file their financial statements annually with the national corporate registry. However, prior to that Act, this was only a requirement for public firms. Certain small or medium-sized companies may prepare accounts for their members under the special provisions of sections 246 and 246A of the Companies Act 1985.[3] In addition, they may prepare and deliver abbreviated accounts to the Registrar. Public companies (as well as certain companies in the regulated sectors) cannot qualify

[1] This section is primarily based on the discussion in Ball and Shivakumar (2005) and Brav (2005).

[2] The main functions of Companies House are to "incorporate and dissolve limited companies; [to] examine and store company information delivered under the Companies Act and related legislation; and [to] make this information available to the public."(http://www.companieshouse.gov.uk/about/functionsHistory.shtml)

[3] The Companies Act 1985 was amended in 1989. The Companies Act 2006 overrules the Companies Act 1989 and, even though intends to simply regulations, could not be implemented immediately but continued through 2007. The new Act makes public companies subject to more stringent regulation whereas relaxes the requirements for private companies. (For further reference to the Companies Act 2006, please visit the Office of Public Sector Information in UK http://www.opsi.gov.uk/acts/acts2006/).

as small or medium-sized companies.[4] Similarly, companies which are part of a group which has members who are public companies or certain companies in the regulated sector cannot qualify as small or medium-sized. For the other companies, to be classified as small (medium), they must fulfill two of the following criteria for two consecutive year: annual turnover must be GBP 5.6 million (GBP 22.8 million) or less; the balance sheet total must be GBP 2.8 million (GBP 11.4 million) or less; the average number of employees must be 50 (250) or fewer.[5]

Sections 221-242 of Companies Act 1985 provide guidelines as to how financial statements of private and public companies have to be submitted. For example, public companies have to file within 10 months of their fiscal year, private firms within 7 months, respectively. For both types of firms, these statements have to be prepared in accordance with UK accounting standards. If a companies' annual sales exceed GBP 1 million (and all of our sample firms easily passed this threshold), the financial statements have to be audited.[6]

Similarly, UK tax laws do not differentiate between public and private firms as to how financial statements have to be prepared. Even though there are additional disclosure requirements for public companies by the London Stock Exchange, these listing rules do not mandate accounting standards for financial reporting. Overall, financial reporting, as required by the UK regulatory regimes, are equivalent for private and public firms which should bias us against finding a loan cost difference between public and private firms.

The London Stock Exchange offers two markets for listings: (i) the Main Market and (ii) the Alternative Investment Market (AIM). The AIM was launched in 1995 for smaller growing companies. The LSE sets no minimum trading record and does not require a minimum capitalization, asset size, age or free float for admission to AIM. Further, companies admitted to AIM are exempt from seeking shareholder approval prior to substantial share transactions (except reverse takeovers or disposals resulting in a fundamental change of business). Companies, however, need a nominated broker who organizes the flotation and a nominated advisor (Nomad) who supervises the flotation and advises the companies after listing. There is no further regulatory oversight by the Financial Services Authority (FSA), which oversees the Main Market.

Information about admissions to the AIM (new admissions, transfers from the main list and re-admissions) and delistings (going privates and transfers to the main list) for the 2001 to 2009 period reveal some interesting patterns. The number of admissions to the AIM increased from 177 in 2001 to 462 in 2006. However, after the 2008 - 2009 period, admissions decreased to 114 in 2008 and 36 in 2009, respectively. The number of delistings also increased from 72 in 2001 to 227 in 2006 and even increased to 258 (293) in 2008 (2009). More interestingly, the percentage of transfers

[4]For detailed explanatory notes on reporting requirements and disclosure exemptions please refer to http://www.companieshouse.gov.uk/about/gbhtml/gba3.shtml#three).

[5]For fiscal years ending earlier than January 30th, 2004, the following criteria were valid: annual turnover must be GBP 2.8 million (GBP 11.4 million) or less; the balance sheet total must be GBP 1.4 million (GBP 5.6 million) or less; the average number of employees must be 50 (250) or fewer.

[6]Before June 2000, the threshold was GBP 350,000.

from or to the main stock exchange list decreased, for example, from 10 percent of delistings in 2001 to 3 percent in 2009. These findings suggest that firms that are listed on the AIM may be very different from firms that go public on the main market.

2. Methodological Aspects of Propensity Score Estimation

Our approach to assessing the debt cost of being private is to answer the following question: Do public firms, ceteris paribus, pay less for their loans than comparable private companies? In answering this question we recognize a potential selection bias since a firm's decision to be public or private is unlikely to be exogenous, but rather be related to observable characteristics such as firm size or age. Accordingly, following Rosenbaum and Rubin (1983) we use propensity score matching as a way to reduce selection bias. Such matching allows a comparison of outcomes to be performed using treatment and control groups which are as similar as possible.[7]

We identify two groups: public firms (the treatment group, denoted $T_i = 1$ for firm i) and private firms (the control group, denoted $T_i = 0$). The treatment group is matched with the control group on the basis of its propensity score:

$$P(x_i) = Prob(T_i = 1|x_i), with(0 < P(x_i) < 1)$$

The propensity score matching method uses $P(x_i)$ or a linear function of the propensity score, to select controls for each firm in the treatment group.

There are several advantages of propensity score matching methods over conventional regression methods (e.g. multivariate regression models) used in the literature. First while commonly OLS utilizes the full sample for estimation purposes, propensity score matching confines estimation to the matched sub-samples. Using only matched observations reduces the estimation bias vis-a-vis unmatched samples and estimators are generally more robust to model misspecifications (Conniffe, Gash, and O'Connell (2000), Rubin and Thomas (2000)). This is particularly important in our setting where there is an elevation at the boundaries of the propensity score which, in turn, makes it harder to find good matched samples. Second, the matching method does not impose any specific functional form as to the relationship between outcome and control variables. Third, in OLS regression, one usually looks for variables determining the outcome which are also exogenous, by contrast, in propensity score matching, one looks for two sets of control variables, the predictors of participation and predictors of outcome. Rubin and Thomas (2000) have also shown in simulations that variables which are weak predictors of outcome reduce the bias in estimating causal effects using propensity score matching. Consequently, we follow a three step procedure. First, we identify

[7] The more recent banking and corporate finance literature uses propensity score matching to correct for self selection bias. Bharath, Dahiya, Saunders, and Srinivasan (2008) use propensity score matching to identify the impact of lending relationships on loan spreads and Drucker and Puri (2005) assess the impact of bundling of investment banking and commercial banking services on loan spreads. Michaely and Roberts (2007) apply propensity score matching to a large set of UK companies. They study dividend policies in public and private firms.

the determinants of participation and outcome. Second, we estimate the propensity score and third, we estimate the effect of being public rather than private on the cost of loans. We employ Nearest Neigborhood estimation and Local Linear Regression (LLR) as matching methods as described in Heckman, Ichimura, and Todd (1997), Heckman, Ichimura, and Todd (1998) and Fan (1992). We explain these methods as we proceed. Overall, there are merits in using propensity scores over OLS to estimate the loan cost disadvantage of being private.

2.1. Estimating the propensity score

An obvious limitation of this approach is that the corporate structure choice may be endogenous. Firms determine whether they want to be public or private. Initially, we use Propensity Score Matching to reduce a potential selection bias in estimating the causal effects of being public on loan spreads. First, we estimate a probit model including variables determining the outcome (i.e. loan spreads) as well as variables determining participation (i.e. the decision to be public). Brav (2005) and Michaely and Roberts (2007) address firms' self-selection as to legal form using a probit model in their first stage regressions. They also look at UK companies and we use the same variables used by these authors as determinants of participation.[8]

We estimate a probit model of the following form,

$$PUBLIC = \beta_0 + \sum \beta_i (Borrower_i) + \sum \beta_j (Loan_j) \sum \beta_k (Controls)$$

where *Public* is a dummy variable equal to either 0 or 1. Borrower characteristics include the log of borrower size, interest coverage, leverage, tangibility, a dummy whether the borrower is investment grade or not rated, profitability, growth, cash, assets and age. Loan characteristics include the log of loan size, maturity, dummy variables for loan type, loan purpose, refinancing, secured and covenants.

We then use the results from the probit regression to calculate a borrower's propensity score, i.e. the probability that a firm is public given our set of control variables. In order to match private and public companies based on their propensity scores, there needs to be a sufficient overlap in the propensity scores for each type of borrower. Accordingly, we impose a common support condition, i.e. we do not match public firms whose propensity score is larger than the largest propensity score among private firms, and we do not match private firms whose propensity score is smaller than the smallest score among public firms. This has an important implication, namely, the more the propensity scores for private and public companies are concentrated at the extreme boundaries (that is, 0 and 1), the less likely it is we will find sufficiently good matches and the more observations will be dropped from our sample.

Figure 1 shows the distribution of public and private firm propensity scores. The graph shows

[8] The variables which most likely determine participation are PROFITABLITY, GROWTH, LOG(CASH), LOG(ASSETS), LOG(1+AGE) and year and two digit SIC Codes.

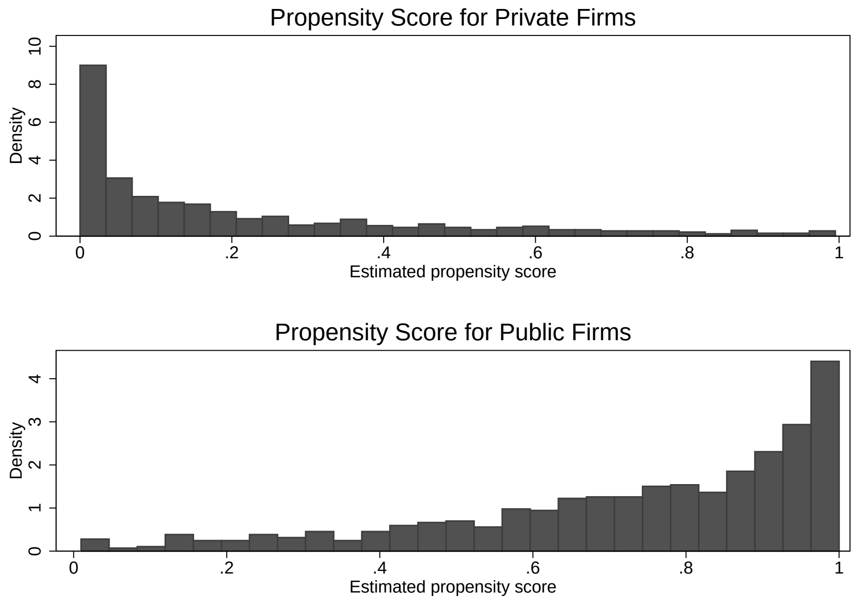

Figure 1: Histogram of Propensity Score

an elevated concentration of the propensity scores at the boundaries, but also a sufficient overlap between private and public companies in-between.

In order to obtain robust results from our analysis, we use two different matching methodologies to evaluate the cost of being private: nearest neighbor and local linear matching which we discuss below.

2.2. Nearest Neighbor Matching

The first class of matching estimators we use is nearest neighbor matching. For each loan to a public firm, the nearest neighbor matching chooses the loan to a private firm that is closest in terms of its propensity score (this loan is called the ”neighbor”). The literature proposes several variants of this matching procedure, e.g. matching ”with replacement” and ”without replacement” and ”oversampling”, i.e. using more than one nearest neighbor. In the case of the nearest neighbor matching with replacement, the loan to a private firm can be used more than once as a match. If the matching is done without replacement, each loan can only be considered once. If we allow for replacement, the quality of the match will increase, particularly, if the propensity scores are asymmetrically distributed among public and private firms as was shown in Figure 1. Intuitively, if we do not replace the matched private loans, it is likely to be the case that we may match relatively high score loans to public firms with low score loans to private firms. This would be a weak match and matching with replacement mitigates this problem.[9] A second variant of nearest neighbor matching is to increase the number of neighbors used in the matching procedure. This is advantageous because more information is used to construct the match. Additionally, if there are many loans to private firms with propensity scores comparable to the loan to the public firm (”comparison units”), it does not reduce the quality of the match. In the following analysis we do both, i.e. we use matching with replacement to account for the characteristics of the propensity score distribution in our sample. Further, we use 50 and 100 nearest neighbors to match loans to both types of firms.[10]

The results are tabulated in Appendix Table 1. We always report the cost savings of a public firm (the coefficient of PUBLIC) whose absolute values correspond to the relative spread cost of being private. Panel A reports coefficient estimates from PUBLIC using nearest neighbor (NN) matching with 50 (100) neighbors. For each method, we report results without bootstrapped standard errors as well as using bootstrapped standard errors with 50 (100, 300) replications. The results show significant loan cost savings for public companies: matching with 50 (100) nearest neighbors suggests that public firms save 26bps (46bps) compared to private firms. As a higher number of neighbors calculates the average loan spread of the matched group of private firms over a broader range of propensity scores, our results suggest that the difference in loan spreads between private and public companies depends on the propensity of being public. This is interesting as it brings up the question as to whether the cost of being private is smaller when propensity scores are high or low, i.e. when firms have a higher or lower propensity of being public. Intuitively, we expect the spread difference to be smaller when propensity scores are high because private companies with high propensity scores are supposed to be more transparent relative to private companies with low propensity scores, and, consequently, information about these firms is available at lower costs for investors. We test this hypothesis in section 5. For robustness, we repeat our analysis using local linear matching as an alternative matching procedure. In particular, local linear matching has certain advantages over nearest neighbor matching when a large number of propensity scores are at the boundary.

2.3. Local Linear Matching

In the previous section, we used a matching procedure where the number of loans to private firms that are used to construct the match was limited by the number of nearest neighbors we imposed on the matching process (50 or 100). Here, we use the local linear estimator that uses weighted averages of *all* loans to private firms to construct the matched sample. Basically, these weights are a function of the distance between the propensity score of the loan to the public firm

[9]However, as Smith and Todd (2005) note, matching with replacement increases the variance of the estimated effect because this procedure reduces the number of distinct loans to private firms used to construct the match.

[10]This method is in line with prior research in this area (Drucker and Puri (2005), and Bharath, Dahiya, Saunders, and Srinivasan (2008)) and accounts for the asymmetric distribution of the propensity score in our sample.

and the propensity score of each of the loans to the private firms, with loans to private firms with propensity scores similar to that of the public firm receiving the highest weight. The larger this distance between the public and private firm scores, the lower the weight. However, using all observations also implies that weak matches (with a large distance between the propensity scores) are also incorporated in the calculation of the loan cost difference. Therefore, it is essential to impose the same common (support) restriction as explained above, regarding propensity score overlap. We use the local linear estimator as proposed in Heckman, Ichimura, and Todd (1997) with a Gaussian kernel.[11]

The results are tabulated in Panel B of Appendix Table 1 (we report standard errors without bootstrapping as well as standard errors obtained by bootstrapping with 50 (100,300) replications). Local linear matching shows that public firms pay 60bps lower spread than private firms and the difference is highly significant. This confirms our earlier result that loan spreads are higher for private than for public firms.

3. Instrumental Variables and Treatment Effects models with more instruments

In further tests, we use two additional instruments. We use a variable that proxies for the visibility of the firm and include the natural logarithm of one plus the number of public firms in the same 2-digit SIC code as a percentage of all public UK based companies as an additional instrument. We also include a lagged variable of being public indicating that the firm has already been public for at least three years before loan origination. The high transaction costs associated with going public makes this a potentially good instrument. We estimate the instrumental variable model using these instruments.The F-statistic of the first stage is significant at the one percent level which rejects the null hypothesis that all instruments are zero. We test the overidentifying restrictions using a NxR^2 test where N is the number of observations and R^2 is the R^2 from the regression of the residuals from the second stage regression on all of the exogenous variables and the instruments. This test is distributed χ^2 with degrees of freedom equal to the number of overidentifying restrictions (in our case 2). We cannot reject the hypothesis that the instruments are uncorrelated with the error term of the spread equation. We also use a difference-in-Sargan test, treat each of the instruments in turn as potentially endogenous and test for orthogonality of each instrument. All tests reject the null hypothesis that the instruments are endogenous. The treatment effects model gives a similar result. The inverse mills ratio is insignificant indicating that unobservable borrower characteristics do not affect loan spreads.

[11] Local linear matching is similar to the kernel estimation but adds a linear term in the propensity score which is helpful when data are asymmetric. Concentration of observation around the boundary points is an asymmetry which arises in our data which makes this matching method appealing. As shown by Fan (1992), the local linear estimator converges faster at the boundary points than the kernel estimator due to the linear term. For a detailed discussion of the differences between the local linear and the kernel estimator and simulations analyses of matching methods see Fan and Gijbels (1996) and Froelich (2004).

4. Extended Discussion of the Channels of the Loan Cost Disadvantage of Being Private

In this section, we provide an extensive discussion of the channels that affect the loan cost difference between private and public firms. We repeat the basic regressions results shown in Table 6 in the paper and extend the results using different proxies and tests.

4.1. Lower Cost of Information Production

4.1.1. Bond Market Access

We start by analyzing the effect of bond market access on loan spreads. A substantial amount of information about the creditworthiness of a firm is revealed when the firm issues bonds through filings to register the bond, information disclosed by underwriters to place the firm's bond, pricing of its bonds, bond analysts reports and through credit ratings. This information is likely to have an impact on loan spreads as well as the information about the riskiness of firms that debt market investors are concerned about (Hale and Santos (2009)). Therefore, we use the cross-sectional variation of private and public firms which have or have not issued public debt in the past to analyze the informational effect of public debt on loan spreads and the loan cost disadvantage of private firms.

First, we ask whether having issued public bonds lowers the cost of private debt. Appendix Table 2 reports the regression results. All variables used in this and any further tests are defined in Appendix Table 10. We construct three different measures for bond market access: *Bonds* is a binary variable equal to 1 if the firm has issued public bonds in the past. *Last Bond Public* is a dummy variable equal to 1 if the firm's last bond issue before the loan origination has been public. *Log(1+Prior Bonds)* is the natural logarithm of 1 plus the number of prior public bonds the firm has issued prior to the loan origination date. Consistent with our prior results, we find that public firms pay 27bps lower loan spreads compared to private firms. However, initially (column 1 to 3) we do not find evidence that having issued public debt affects loan spreads. We add the interaction term of *Public* and our measures for bond market access in columns (4) to (6). For example, in column (4), the coefficient of *Bonds* indicates that having access to the public debt market reduces spreads on private firm loans by 46bps, which is economically meaningful and statistically significant at the 1 percent level. However, the coefficient of *Bonds x Public* is positive and significant and of similar magnitude. A Wald test cannot reject the null hypothesis that both coefficients are identical (p-value is 0.901). A similar interpretation can be extended to the other proxies for bond market access in columns (5) and (6). These results are consistent with access to public debt lowering the cost of information production for investors translating into lower spreads for private firms.

If bond market access lowers the cost of debt for private (and not for public firms), it is a natural question to ask whether the loan cost disadvantage of being private still persists if private firms have access to the public debt market. We test this hypothesis in column (7) where public firms with bond market access are the omitted group. We find that public firms without bond market do not pay significantly different loan spreads, but, more importantly, private firms which have issued public bonds before loan origination also pay similar loan spreads compared to public firms with public bonds. In other words, they do not experience a loan cost disadvantage because sufficient information is revealed about these firms upon the issuance of public debt. Private firms without public bonds, however, pay 34pbs higher loan spreads compared to public firms with public bonds and this result is significant at the 1 percent level.

4.1.2. Stock Exchange Listings

We investigate the informational effect of being listed on exchanges with different degrees of disclosure requirements as a second mechanism that can explain the loan cost disadvantage of being private. We have two groups of public firms. First, we have *FTSE 100* and *FTSE 250* companies which can be thought of as the most transparent firms.[12] The second group of public firms comprises all other segments, i.e. Small Cap, Other and AIM. In particular, we are interested in the spread difference between this group of less transparent public firms and private borrowers, after controlling for observable borrower and loan characteristics.

We report descriptive statistics for firms within the different trading segments on the Main Market (*FTSE 100, FTSE 250, Small Cap, Other*) and the Alternative Investment Market (AIM) in Panel A of Appendix Table 3. We also include the descriptive statistics for private firms with and without bond market access. As can be seen, the FTSE 100 and FTSE 250 firms from the Main Market are much larger in size, pay on average lower spreads, have a more widely dispersed ownership structure and borrow at shorter maturities compared to all other firms on the Main Market, on *AIM* and also private firms. Interestingly, while private firms are on average much larger in size than firms traded on the *Small Cap* and *Other* segments of the Main Market and the *AIM*, our univariate tests suggest they pay on average much larger spreads.[13]

Panel B of Appendix Table 3 reports the regression results where *FTSE 100/FTSE 250* is a dummy variable equal to one if the firm's equity is traded as part of these indices. Column (1) shows the results. As can be seen, *FTSE 100/ FTSE 250* firms pay 32bps lower spreads than other public borrowers. We also analyze the loan spread differences between the two public firm cohorts and our private sample firms in column (2) where private firms are the omitted group. We find that FTSE 100/FTSE 250 firms pay on average 39bps lower spreads than private borrowers. Interestingly,

[12] *FTSE 100* and *FTSE 250* firms represent 96% of the UK market capitalization (http://www.ftse.com/Indices/UK_Indices/index.jsp).

[13] Furthermore, reporting the results separately for private firm with (*Bonds*) and without (*No Bonds*) bond market access, we find that firms that have issued public bonds in the past are even larger in size than *FTSE 250* firms but pay somewhat higher spreads on their loans, however, they pay lower spreads compared to, for example, Small Cap or AIM firms. The asset size of private firms without bond market access, on the other hand, is only a quarter of the size of private firms with bond markets access and they pay more than twice their spread, on average.

however, there is no significant spread difference between private firms and Small Cap/Other/AIM firms in a regression setting. In column (3), we further distinguish between private firms with and without public bonds and find that *Small Cap / AIM* firms pay 30bps higher spreads compared to *FTSE 100 / FTSE 250* firms (which are omitted).[14]

Our findings have interesting implications: should not all private firms become public to reduce their borrowing costs? Our results suggest that being listed in and of itself does *not* lower the firm's borrowing costs. Specifically, an IPO that results in a listing in a relatively small secondary market such as the *AIM* does not reduce a firm's borrowing costs.[15]

4.2. Bargaining Power

Do public firms have more bargaining power vis-a-vis their lenders compared to private firms? Or, to say it differently, can the loan cost disadvantage of private firms be explained by lenders exploiting their informational advantage? Rajan (1992) and Sharpe (1990) argue that the private information banks gain through monitoring allows them to informationally capture these firms.[16]

We follow the earlier literature in defining whether or not a bank is a relationship lender. A bank is a relationship lender if it had a lead position among the syndicate members in a loan to the same borrower during the past five years prior to the current loan (see e.g. Ljungqvist, Marston, and Wilhelm (2006), Bharath, Dahiya, Saunders, and Srinivasan (2008) and Schenone (2010)). Since syndicated loan deals typically involve one or more lead role banks, our measure of relationships is a binary variable that is assigned the value 1 if one of the lead banks in the current loan syndicate is a relationship lender (*Rel(Dummy)*). We further use intensity measures to proxy for the strength of the relationship. *Rel(Number) (Rel(Amount))* is the ratio of the number of loans (amount of

[14] Consistent with our earlier result, we also find that private firms with access to bond markets do not pay higher spreads compared to *FTSE 100 / FTSE 250* firms. Private firms without public debt, on the other hand, pay 62bps higher loan spreads than the omitted group of firms. Private firms that have issued bonds have more information readily available for investors relative to *Small Cap/AIM* firms which leads to lower relative costs of private debt. In unreported tests, we also use the number of analysts that issue earnings forecasts about a public borrower at the time of the loan as proxy for information ability about public firms. A testable hypothesis is that the loan cost difference between public and private firms should be lower if public firms have low analyst coverage. We obtain these data from I/B/E/S. We still find that public firms pay lower loan spreads than private firms. However, we do not find evidence to support our hypothesis, i.e. analyst coverage does not significantly influence spreads on loans received by public firms, a result consistent with banks having superior monitoring and information advantages compared to outside analysts.

[15] This is in line with Asker, Farre-Mensa, and Ljungqvist (2010) who provide related evidence that, even if the IPO reduces a firm's borrowing costs, increased agency costs of being public has adverse economic consequences such as a reduction in a firm's investment incentives which outweighs the advantage of a lower cost of capital.

[16] There is some empirical evidence supporting the assumption that relationship lenders have private information about their clients that is not easily available to outside lenders. James (1987) and Lummer and McConnell (1989), for example, show that bank loan announcements (particularly renewal of loans) convey information to lenders which is consistent with banks having private information from repeat lending relationships. Houston and James (1996) provide evidence for firms with long-term debt outstanding consistent with the hold-up problem. Sufi (2007) finds that lead arranger private information is important in a syndicated loan setting. Santos and Winton (2008) identify significant hold-up costs for bank dependent borrowers.

loans) extended by the lead arranger to the same borrower as a percentage of the total number of loans (total loan amount) this borrower received in the past 5 years prior to loan origination.

Appendix Table 4 reports the regression results. Public firms still pay on average 27bps lower spreads even after including the three relationship measures as shown in columns (1) to (3). The coefficients on the relationship variables are positive and significant at the 5 or 10 percent level. In columns (4) to (6), we interact these variables with *Public* to identify the effect of relationships for private vis-a-vis public firms. We find a different effect of relationships for private relative to public firms. For example, column (4) shows that private firms borrowing from a relationship lender pay, on average, 22bps higher spreads relative to non-relationship borrowers. This result is consistent with Schenone (2010) who also identifies higher loan spreads for firms before they go public and suggests that lenders exploit their informational advantage by imposing higher spreads. The average public firm, on the other hand, does not benefit from borrowing from a relationship lender. The sum of the coefficients of *Rel(Dummy)* and the interaction term is insignificant. This result is consistent with Bharath, Dahiya, Saunders, and Srinivasan (2008) who find that relationship benefits dissipate for transparent public firms.[17]

We next ask whether issuing public bonds in a prior period levels shifts bargaining power such that the relationship banks begin to share relationship benefits with their clients. To explore this we introduce *Private*, a binary variable equal to 1 if the firm is private and assess the impact of being private conditional on both borrowing from a relationship lender and having issued public debt before loan origination. Consistent with prior results, we find that the secular effect of being private on loan spreads is positive and, on average, 24bps and significant at the 1 percent level. Further, spreads are higher when private firms borrow from relationship lenders but lower when they have access to public debt. More interestingly, however, is the coefficient on the triple interaction term (*Rel(Dummy) x Private x Bonds*) is negative and significant which suggests that even private firms can benefit from borrowing from relationships lenders, conditional on having issued public bonds in the past.[18] Even without relationships, private firms with bonds have lower loan spreads compared to private firms without access to bond markets. Our results therefore suggest that lending relationships is another important mechanism in explaining the loan cost disadvantage of private firms.

4.3. Ownership Structure

A third mechanism that can explain loan spread differences between public and private firms are differences in ownership structure between public and private firms. In this section, we examine two important aspects of ownership structure on bank debt costs: (i) inside ownership concentration

[17] For example, Bharath, Dahiya, Saunders, and Srinivasan (2008) document that rated (public) firms do not receive a loan cost related benefit from relationships.

[18] These results are consistent with Hale and Santos (2009) who find that bond IPOs mitigate information monopolies by relationship lenders.

and (ii) private equity ownership.

4.3.1. Inside Ownership Concentration

The mechanisms as to how a firm's ownership structure influences its cost of capital is related to the corporate governance literature on: (1) ownership concentration and corporate risk taking and (2) ownership structure and takeover likelihood. For example, Amihud and Lev (1981) argue that there is a positive relationship between insider ownership and risk taking because the interests of managers and shareholders become more aligned. Their results imply that loan spreads and ownership are negatively correlated.[19] A second strand of literature analyzes the link between ownership concentration and takeover likelihood. For example, Song and Walkling (1993) argue that this relationship is negative: the higher the percentage of insider equity ownership the less likely it will be that the company is a takeover target.

We collect data on firm ownership from Bureau van Djik's "Ownership" database which provides approximately 15 million active direct owner and subsidiary links.[20] The database provides a list of shareholders with their percentage of ownership and the ultimate owner of the firm (i.e. the shareholder with the highest percentage of ownership provided that this company itself does not have a single shareholder with more than 24.99 percent of ownership). The different types of shareholders recorded in the database include banks, financial/insurance companies, fund families[21] as well as firm directors/employees/managers. Overall, we are able to identify ownership data for 62% of the firms in our sample, which corresponds to 300 firms (175 public and 125 private firms) and 1,063 loans.

We use the natural logarithm of the number of reported shareholders (*Log(Owners)*) as a proxy for ownership concentration.[22] The results are reported in Appendix Table 5. Even after controlling for ownership, private firms still pay 21bps higher loan spreads than public firms (column (1)). However, ownership structure itself is an important factor in explaining loan spreads. For example, increasing the number of shareholders from the highest to the lowest ownership concentration quartile reduces loan spreads by 25bps. As the variation in the number of shareholders is rather limited in the subsample of private firms, we run our tests separately for private and public firms instead of using interaction terms. The results are reported in columns (2) and (3) of Appendix

[19] However, this relationship might be non-monotonic as suggested by Wright, Ferris, Sarin, and Awasthi (1996). That is, the relationship between insider ownership and risk taking might be positive at first but later on be negative because (a) too much of the manager's personal wealth is tied up in the firm so that inside owners prefer less risk and (b) managers become entrenched and (due to non-financial benefits and costs) pursue non-value maximizing strategies.

[20] Figures refer to August 2007. About 20,000 new links are added each month.

[21] Unfortunately, there is no percentage ownership of family shareholdings available for the companies in our dataset. Thus, we are unable to separate family-owned firms from the rest of the sample.

[22] Note that this number does not include private (unnamed) shareholders. The database only reports the aggregated percentage ownership of these shareholders. The average number of reported shareholders for public (private) firms is 40.42 (2.48) with a standard deviation of 26.13 (3.98). In addition, 75% of public (private) firms have less than 61 (2) shareholders and the maximum number of shareholders is 93 (38).

Table 5. The coefficient on the ownership variable is insignificant in the subsample of private firms (column (3)) but highly significant and negative in the public firm sample (column (2)).

We use the Herfindahl-Hirshman-Index (*HHI*) as an additional proxy of ownership concentration and calculate the *HHI* with the percentage ownership share of each reported shareholder. We divide our sample of public firms into public firms with high and low ownership concentration and compare their loan spreads to spreads on loans to private firms.[23] We define ownership concentration as follows: ownership concentration is high (low) if the *HHI* is above (below) 0.67. Public firms with highly concentrated ownership are then comparable to private firms.[24] In column (4), we introduce two interaction terms, where *Public x HHI(LOW)* is a dummy variable equal to 1 if public firms have low ownership concentration, and where *Public x HHI(HIGH)* is a dummy variable equal to 1 if the public firms have high concentrated ownership. Private firms are the omitted group. We find that even public firms with high ownership concentration still pay, on average, 40bps lower loan spreads than private firms and this result is significant at the 1 percent level and economically meaningful. To summarize our results, we find that concentrated (insider) ownership can potentially explain higher spreads of private firm loans.

4.3.2. Private Equity Ownership

The UK experienced a dramatic increase in buyout activity during the last years of our sample period: the deal value increased from GBP 17bn in 2003 to GBP 45bn in 2007.[25] Companies that are owned or managed by private equity firms may well be inherently different than other firms and this difference might might be reflected in loan spreads. Specifically, private equity financed firms employ a higher level of leverage increasing firm bankruptcy risk.[26] This is likely to be particularly severe for smaller, private firms. In order to examine the impact of private equity firms, we supplement our data by tracking private equity involvement/ownership for each individual company.

To do this we need to rely on a number of different data sources. First, LPC Dealscan contains the field ”loan purpose comment”, which gives information about whether the deal is a buyout transaction, and ”sponsor”, which indicates the name of the private equity sponsor(s) involved in the transaction. We obtain information about all public-to private transactions (PtP) in the UK from Mergermarket and complement these data with information from Hoover’s Corporate History database. We further check, for each company name, the investments listed on the websites of the

[23] We do not split our private firms into low versus high ownership firms because there is only little variation in the ownership measure.

[24] For example, the average number of shareholders of private and public firms with highly concentrated ownership is 2.2 and 4.5, respectively. For comparison, the average number of shareholders of public firms with low concentrated ownership (lowest tercile) is 54.2.

[25] Center of Management Buyout Research, http://www.nottingham.ac.uk/business/cmbor/

[26] For example, we find that the relative loan size (as percentage of total assets) is 23% larger for buyout transactions compared to other deals.

private equity sponsors and press articles using various sources (Factiva, Business Week, etc.). For each loan, we know exactly whether the associated deal is either (i) a PtP, (ii) a LBO/MBO (other than a PtP), (iii) an acquisition or (iv) a recapitalization. We provide some descriptive statistics of these deals below.

Our data show that 17% of all loans received by public firms are associated with PtP transactions, only 1% with LBO/MBO transactions and 1% with other private equity backed transactions such as acquisitions or recapitalization. There is no private equity firm at all involved in 81% of the loans in our sample. However, 66% of the loans to private firms have some private equity participation. The majority of these private firm loans (49%) are associated with LBO/MBO's and 17% with other private equity backed transactions.

The effects of private equity involvement are reported in columns (5) and (6) of Appendix Table 5. The regressions include the following variables to control for private equity involvement: *PtP* is a dummy variable equal to 1 if the firm is taken private, *LBO/MBO* is a dummy variable equal to 1 if the deal is a buyout but the firm is not taken private, and *Private Equity (Not Buyout)* is a dummy variable equal to 1 if the deal involves a private equity sponsor, but is not a buyout transaction. Our major finding, that private firms pay higher spreads compared to public firms, still holds, i.e. private firms pay approximately 24bps higher spreads than public firms and this difference is highly significant (column (5)). Nevertheless, the influence of private equity participation on loan spreads is considerable with private equity owned firms paying 55bps to 85bps higher spreads relative to those firms free of private equity participation.

A natural question that arises is what is the loan spread difference between private and public firms without private equity involvement? Further, what is the difference in spreads between public companies backed by private equity firms and non-private equity backed private firms? If private equity involvement increases loan spreads, the loan spread disadvantage of private firms should be reduced once this effect is controlled for. To examine these questions, we include the interaction term *Public x Private Equity* in our regression. This interaction term is equal to 1 if the firm is public and the deal involves a private equity sponsor. This variable captures all deals of public firms with private equity participation. The results are reported in column (6) of Appendix Table 5. Three interesting results emerge: First, if no private equity is involved, private firms pay 26bps higher loan spreads compared to public firms and the difference is significant at the 1 percent level. This is consistent with our earlier results that information imperfections are of a first order importance in explaining the loan cost disadvantage of private firms. Second, private firms managed or owned by private equity pay 66bps higher loan spreads compared to private firms that are not backed by private equity. This is consistent with banks demanding a premium for investing along with private equity firms. Third, the diagnostic section of Appendix Table 5 reports the Wald test under the hypothesis that spreads for public firms backed by private equity are not significantly different from spreads paid by private firms with private equity involvement. We cannot reject this hypothesis at a meaningful level of confidence (p-value is 0.945). This corresponds to our earlier intuition that the spread difference is reduced (and even disappears) if deals by public firms involve private equity.

Taken together, there is evidence that ownership and/or governance of firms is an important channel through which loan spreads can be affected.

4.4. Secondary Market Trading

A fourth channel that can explain the loan cost disadvantage of private firms relates to whether or not loans are traded in the secondary loan market after origination. Selling a proportion of the loan allows lenders to hedge their exposure to one particular borrower or industry ("diversification" effect), which, ceteris paribus, should reduce loan spreads. There is also substantial evidence that banks get access to private information when they extend loans to firms (James (1987), Lummer and McConnell (1989), Best and Zhang (1993), and Billett, Flannery, and Garfinkel (1995)). Secondary loan prices reveal information about the firm to investors and may lead to a reduction in the cost of debt ("information" effect), for example, by reducing the information premium demanded by banks or by reducing the informational advantage of relationship banks (Rajan (1992)). An alternate argument highlights that banks are able to reduce their exposure to borrowers by selling (a portion of) their loan share in the secondary market. In the syndication process, lead banks retain a share of the loan as commitment device to diligently monitor the borrower (Sufi (2007) and Bharath, Dahiya, Saunders, and Srinivasan (2007)), which might be effectively reduced. If loan trading undermines monitoring, the scope for risk shifting is increased. This might lead to a wealth transfer from debtholders to shareholders and thus to higher spreads demanded by lenders ("monitoring" effect). In other words, loan sales might increase or decrease the loan cost disadvantage of being private.

To examine this, we supplement our dataset using daily secondary market loan prices for the 1999 to 2007 period from the Loan Syndication and Trading Association (LSTA) and Loan Pricing Corporation (LPC) market-to-market pricing service.[27] This dataset includes daily bid and ask quotes aggregated across dealers, the number of dealers providing bid and ask quotes, a unique loan identification number (LIN), the borrower name, the loan type and the pricing date. Panel A of Appendix Table 6 provides some descriptive statistics about the distribution of loans in our sample that have been traded after origination for both cohorts, private and public firms. We refer to loans that have been traded as "traded" and those that have not been traded as "not traded", respectively. On average, 10% of all loans in our sample are liquid, and the percentage is even higher for loans received by private firms, i.e. 12.5% versus 7.8% for loans received by public firms. Until 1999, secondary loan trading was virtually non-existent in Europe as reflected also in our sample. Even between 1999 and 2002, only a small number of loans were traded after origination.[28] Those

[27] For more details about the secondary loan market and this dataset see for example Gande and Saunders (2010) and Wittenberg-Moerman (2005).

[28] Gadanecz (2004) reports that, in 2003, about 11% of all loan originations in UK were traded in the secondary

loans that were traded were predominantly loans to public firms. Since 2003 and, particularly, during the last three years of our sample period (2005-2007), a growing number of loans to private firms have been actively traded in the secondary loan market reflecting the substantial increase in buyout activity in the UK.[29]

We add the dummy variable *Traded* which takes the value 1 if the loan is traded in the secondary loan market after origination to our regression. The results are reported in Panel B of Appendix Table 6. Column (1) shows that traded loans have 30bps higher loan spreads which is consistent with the monitoring effect described above.[30] Arguably, private firms are inherently more opaque and more difficult to monitor. For such firms, the risk shifting problem should be more relevant. In Column (2), we test this hypothesis by adding the interaction term *Public x Traded* to the regression. We document that the coefficient of the interaction term is negative and significant. We test the null hypothesis that the magnitude of the coefficients of *Traded* and the interaction term are identical and cannot reject this hypothesis at a meaningful level of confidence (p-value is 0.252). While traded private firm loans have higher loan spreads relative to non-traded loans, we cannot find a statistically significant difference between traded and not-traded public firm loans. Taken together, secondary market trading is a channel that can explain the loan cost disadvantage of private versus public firms.

4.5. Future Performance

The final potential mechanism we analyze is differences in expected future performance of private versus public firms. Our hypothesis is that loans to private firms have higher loan spreads because public firms are less risky than private firms or they differ in terms of their future investment opportunities. Lenders might anticipate these performance differences and ex-ante demand higher spreads for private firm loans. To examine this, we calculate 1, 2 and 3 year sales growth rates for private and public firms and use them as additional control variables. The results are reported in Appendix Table 7. Models (4) to (6) also add interaction terms with *Public*. To summarize our results, we do not find evidence that differences in expected future performance prompt lenders to ex-ante increase spreads on private firm loans. We provide further tests and discussions about the ex-post performance of private versus public firms below. However, we first introduce and compare different predictors of firms' default risk.

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loan market. This figure has doubled since 2002.

[29]For example, we find that 14% of loans in our sample that are linked to transactions with private equity firm participation were subsequently traded in the secondary loan market (compared to 7% non-private equity backed deals). The average number of dealers providing bid and ask quotes is 3.2, the average number of trading days is 462 and 68% are non-zero return trading days.

[30]Our results support the findings in Gande and Saunders (2010) who document negative abnormal bond returns around the first trading of a borrower's loan.

5. Predicting the Default Risk of Private and Public Firms

Both the literature and practice suggest different (balance-sheet based) predictors of default risk of a firm. Here, we briefly introduce five different predictors and employ them in the subsample of our public UK firms to assess how well these predictors proxy for the more well-known Z-Score metric: (i) the Original Z-Score (Z), (ii) the Z'-Score (Z'), (iii) the Modified Z-Score (Z_M). We also employ two measures taken from the accounting literature, i.e. (iv) the Zmijewski Score (Z_{ZMI}) and (v) the Ohlson O-Score (O). As some of these measures include market values which are not available in Amadeus, we use Compustat for calculating all scores for our sample of public firms.

1. Original *Z*-Score (Altman Z-Score)

The Z-Score we employ is defined in Altman (1968) and Altman (2000):

$$\begin{aligned} Z &= 1.2(NWC/TA) + 1.4(RE/TA) + 3.3(EBIT/TA) \\ &+ 0.6(MVEQ/BVTL) + 0.999(Sales/TA) \end{aligned}$$

- NWC: Net Working Capital
- TA: Total Assets
- RE: Retained Earnings
- EBIT: Earnings Before Interest and Tax
- MVEQ: Market Value of Equity
- BVTL: Book Value of Total Liabilities

Altman (1968) identifies cutoff values, i.e. firms with a Z-Score of less than 1.81 are likely to fail, firms above 2.99 are likely not to fail, and the firms with Z-Scores in between are "in a zone of ignorance", i.e. firms within this range either failed or survived in the past. The mean Z-Score of our public UK sample firms is 2.97. The Type I (Type II) accuracy in predicting default are 94% (97%).

2. *Z'*-Score (Private Firms)

To calculate a measure for private firms where market values of equity don't exist and avoiding simply substituting book value for market values in calculating the Z-Score of a private firm, Altman re-estimated the model and identifies different coefficient estimates and cut-off values (Altman (2000), Caouette, Altman, Narayanan, and Nimmo (2008)).

$$
\begin{aligned}
Z' &= 0.717(NWC/TA) + 0.8472(RE/TA) + 3.107(EBIT/TA) \\
&+ 0.420(BVEQ/BVTL) + 0.998(Sales/TA)
\end{aligned}
$$

- BVEQ: Book Value of Equity

Even though the coefficients changed, the overall model looks very similar to the original Z-Score model. The revised book value measure is still the third most important contributor. Altman (2000) shows that the Type I and Type II accuracy in predicting default are both almost identical compared to the original model. Interestingly, he finds that the nonbankrupt firms' mean Z'-Score is lower than the original model and this is consistent with what we find in the data. The mean Z'-Score for our public firms is 1.89 (compared to 2.97 in the original model) but the correlation between Z and Z' is 0.65 and highly significant at the 1 percent level.

3. Modified Z-Score (Z_M)

We also consider a Z-Score first modified by Mason (1990) and later employed by several others in the finance literature where the market value of equity term is simply dropped from the model.

$$
Z_M = (1.2(NWC) + Sales + 1.4(RE) + 3.3(EBIT))/TA)
$$

The mean Z_M is 1.99 and very similar to Z'. The correlation between Z_M and Z (Z') is 0.48 (0.79) and in both cases significant at the 1 percent level. We also consider other credit scoring models coming from the accounting literature.

4. Zmijewski Score (Z_{ZMI})

$$
Z_{ZMI} = -4.3 - 4.5(NI/TA) + 5.7(TD/TA) - 0.004(CA/CL)
$$

- TD: Total Debt
- CA: Current Assets
- CL: Current Liabilities

The mean Z_{ZMI} is -0.98. Note that there is a negative association between the previous default predictors and Z_{ZMI} as well as O (see below). That is, higher values of Z_{ZMI} and O correspond to a higher likelihood of default.

5. Ohlson O-Score (O)

$$\begin{aligned} O &= -1.32 - 0.407(Size) + 6.03(TL/TA) - 1.43(NWC/TA) - 2.37(NI/TA) \\ &- 1.83(FUTL) - 1.72(OENEG) - 0.521(CHIN) \end{aligned}$$

- Size: ln(Total Assets)
- TL: Total Liabilities
- FUTL: Funds provided by operations divided by total liabilities
- OENEG: One if total liabilities exceeds total assets, zero otherwise
- CHIN: $(NI_t - NI_{t-1})$ / $(|NI_t + NI_{t-1}|)$

The mean O is -1.12.

Panel A of Appendix Table 8 provides a brief overview of papers using either methodology, Panel B reports the correlation between the different default predictors.

Again, the correlation between Z and Z' is 0.65 and highly significant, i.e. Z' is a good proxy for borrower default risk as a substitute for Z in our setting where market values are not available for private firms. Furthermore, Z' is highly correlated with Z_M (which is the more often used metric in the finance literature) and, therefore, is likely to proxy well for Z_M as well. The accounting literature based default predictors (Z_{ZMI} and O) are somewhat less, but nevertheless highly significantly, correlated with Z , Z' and Z_M.

In a next step, we apply the various default predictors (except the original Z-Score model) to our full sample of private and public firms. Panel C of Appendix Table 8 provides some descriptive statistics of Z, Z', Z_M and O which show that the mean values of our measures in the full sample are similar to the ones reported only for public firms. Panel D of Appendix Table 8, again, reports the correlation between the measures for the full sample and shows similar, sometime even more pronounced results compared to Panel B.

6. Further tests to examine the ex-post performance of private versus public firms

6.1. Ex-post changes in credit quality

To the extent that the relevant unobserved characteristics are related to borrower credit quality, we use changes in Z', Z_M the modified (MacKie-Mason) Z-Score, Z_{ZMI} the Zmijewski Score and O the Ohlson O Score as proxy for ex-post performance. We choose the year of loan origination as the starting point and track the performance for the next 1, 2 and 3 years, respectively.

Panel A of Appendix Table 9 reports the regression results relating changes in the various Z-Score measures to *Public* and other borrower and loan control variables. The accounting data extend to the end of 2007. The latest origination date in our sample is also end of 2007. To address right-censoring concerns, we use loans with the latest origination date of end of 2006, 2005, and 2004 when measuring the performance for t+1, t+2 and t+3, respectively. However, not restricting our sample gives similar results. We lose observations restricting our dataset and whenever all variables required for calculating Z' are not simultaneously available. We include all control variables from Table 4 and allow for clustering of standard errors at the firm level. The coefficient of *Public* is never significant, i.e. we do not find evidence that borrower credit quality changes significantly differently for public relative to private companies over a 1, 2 or 3 year horizon <u>after</u> loan origination.

Actual default rates and rating downgrade probabilities are alternative measures of ex-post borrower performance. If public firms are of higher quality, we expect to find lower default rates and a lower probability of experiencing rating downgrades after loan origination. We obtain rating data from S&P for the 1987 to 2008 period. 327 loans in our sample were issued by rated firms, involving 89 different companies. We observe rating changes over a 1 to 3 year period after loan origination. A borrower is considered to default if a company's credit rating is set to "D". A rating downgrade is defined as a borrower's credit rating dropping by one letter grade, for example, from AA to A. Default events are rare events: Out of these 89 companies, only 4 defaulted by the end of 2008, including 3 public firms. Only 28 firms experienced a credit downgrade, including 20 public and 8 private firms. We estimate a probit model (unreported) using an individual loan as the unit of observation relating rating downgrades to loan and borrower characteristics. Overall, we cannot reject the null hypothesis that private and public firms perform similarly after origination based on this metric.

6.2. Ex-post changes in sales growth

To the extent that relevant unobserved characteristics are related to future growth prospects, we use changes in sales growth as a proxy for ex-post performance. For example, private firms might have more growth options than public firms. If so, we would expect significantly different growth rates for private relative to publicly traded firms. We test this hypothesis using 1, 2 and 3 year sales growth rates as dependent variable and relate them to *Public* and the same control variables used in the prior section. Panel B of Appendix Table 9 shows our results. t+1, t+2 and t+3 indicate the 1, 2 and 3 year sales growth rates, respectively. Again, we do not find evidence that public firms grow differently than private firms.

6.3. Ex-post performance of loans in the secondary loan market

The recent literature in banking and corporate finance discusses the effects of timely information production in secondary markets and the impact on firms' capital structure and cost of capital. For example, Drucker and Puri (2009) analyze the information production in the secondary loan market and identify significant benefits for borrowers as to increased access to capital and more durable lending relationships. Norden and Wagner (2008) examine information production in CDS markets and the impact on loan spreads. Thus, information generated from loan trades might be particularly valuable for the private firms in our sample and secondary market prices therefore a natural candidate to study ex-post performance of private and public firms. We supplement our dataset using daily secondary market loan prices for the 1999 to 2007 period from the Loan Syndication and Trading Association (LSTA) and Loan Pricing Corporation (LPC) market-to-market pricing service.[31] This dataset includes daily bid and ask quotes aggregated across dealers, the number of dealers providing bid and ask quotes, a unique loan identification number (LIN), the borrower name, the loan type and the pricing date.

We match private and public firm loans based on firm size, industry, leverage, loan type, loan vintage year and time when loan comes to secondary market and consider the closest private loan a match. We use daily mid quotes to proxy for the transaction price. To analyze whether or not public firms perform better in the secondary loan market than private firms, we use daily price changes to calculate the returns (R_i) for public and matched private firm loans and examine the cross-section of cumulative abnormal returns (CAR). The CAR for public loan i is defined as

$$CAR_i \equiv \sum_{t=1}^{T} (R_{public,t} - R_{matched-private(i),t}).$$

We calculate returns 1 year after loan origination or when LSTA stops quoting the loan and drop all loans which only have zero return trading days. Cleaning the data results in 48 loans of public firms that can be matched to private firm loans. The results are reported in Panel D of Appendix Table 9. Overall, we cannot reject the null hypothesis that matched private and public firm loans perform equally at a meaningful level of confidence.

[31] For more details about the secondary loan market and this dataset see for example **?** and Wittenberg-Moerman (2005).

References

Acharya, V., S. T. Bharath, and A. Srinivasan, 2007, "Does industry-wide distress affect defaulted firms? Evidence from creditor recoveries," *Journal of Financial Economics*, 85, 787–821.

Altman, E. I., 1968, "Financial ratios, discriminant analysis and the prediction of corporate bankruptcy," *Journal of Finance*, 23, 589–609.

——— , 2000, "Predicting financial distress of companies: revisiting the Z-Score and Zeta models," *Working Paper*.

Amihud, Y., and B. Lev, 1981, "Risk Reduction as a Managerial Motive for Conglomerate Mergers," *Bell Journal of Economics*, 12(2), 605–617.

Asker, J., J. Farre-Mensa, and A. Ljungqvist, 2010, "Does the stock market harm investment incentives?," *Working Paper*.

Ball, R., and L. Shivakumar, 2005, "Earnings quality in UK private firms: comparative loss recognition timeliness," *Journal of Accounting and Economics*, 39, 83–128.

Best, R., and H. Zhang, 1993, "Alternative Information Sources and the Information Content of Bank Loans," *The Journal of Finance*, 48(4), 1507–1522.

Bharath, S., S. Dahiya, A. Saunders, and A. Srinivasan, 2007, "So What Do I Get? The Bank's View of Lending Relationships," *Journal of Financial Economics*, 85, 368–419.

——— , 2008, "Lending Relationships and Loan Contract Terms," *Review of Financial Studies (forthcoming)*.

Billett, M. T., M. J. Flannery, and J. A. Garfinkel, 1995, "The Effect of Lender Identity on a Borrowing Firm's Equity Return," *The Journal of Finance*, 50(2), 699–718.

Bradley, M., and M. R. Roberts, 2003, "The structure and pricing of debt covenants," *Working Paper*.

Brav, O., 2005, "How Does Access to the Public Capital Market Affect Firms' Capital Structure?," *Working Paper, University of Pennsylvania*.

Caouette, J. B., E. I. Altman, P. N. Narayanan, and R. Nimmo, 2008, *Managing credit risk: The next challenge for global financial markets*. Wiley Finance, second edn.

Conniffe, D., V. Gash, and P. J. O'Connell, 2000, "Evaluating State Programmes: "Natural Experiments" and Propensity Scores," *The Economic and Social Review*, 31(4), 283–308.

Dichev, I. D., 1998, "Is the risk of bankruptcy a systematic risk?," *Journal of Finance*, 53(3), 1131–1147.

Drucker, S., and M. Puri, 2005, "On the Benefits of Concurrent Lending and Underwriting," *The Journal of Finance*, 60(6).

——— , 2009, "On Loan Sales, Loan Contracting, and Lending Relationships," *Review of Financial Studies (forthcoming).*

Eisdorfer, A., 2008, "Empirical evidence of risk shifting in financially distressed firms," *Journal of Finance*, 63, 609–637.

Fan, J., 1992, "Design-Adaptive Nonparametric Regression," *Journal of the American Statistical Association*, 87(420), 998–1004.

Fan, J., and I. Gijbels, 1996, *Local Poly nomial Modelling and Its Applications*. Chapman and Hall, London.

Froelich, M., 2004, "Finite sample properties of propensity-score matching and weighting estimators," *Review of Economics and Statistics*, 86(1), 77–90.

Gadanecz, B., 2004, "The Syndicated Loan Market: Structure, Development and Implications," *BIS Quarterly Review*, (December 2004).

Gande, A., and A. Saunders, 2010, "Are Banks Still Special when there is a Secondary Market for Loans?," *Working Paper*.

Graham, J. R., M. L. Lemmon, and J. S. Schallheim, 1998, "Debt, Leases, Taxes, and the Endogeneity of Corporate Tax Status," *Journal of Finance*, 53(1), 131–162.

Hale, G., and J. A. C. Santos, 2009, "Do banks price their information monopoly?," *Journal of Financial Economics*, 93, 185–206.

Heckman, J. J., H. Ichimura, and P. Todd, 1997, "Matching As An Econometric Evaluation Estimator: Evidence from Evaluating a Job Training Program," *Review of Economic Studies*, 64(4), 605–654.

——— , 1998, "Matching As An Econometric Evaluation Estimator," *Review of Economic Studies*, 65, 261–294.

Hillegeist, S. A., E. K. Keating, D. P. Cram, and K. G. Lundstedt, 2004, "Assessing the Probability of Banktrupcy," *Review of Accounting Studies*, 9, 5–34.

Houston, J., and C. James, 1996, "Bank Information Monopolies and the Mix of Private and Public Debt Claims," *The Journal of Finance*, 51(5), 1863–1889.

James, C., 1987, "Some evidence on the uniqueness of bank loans," *Journal of Financial Economics*, 19(2), 217–235.

Leary, M. T., and M. R. Roberts, 2010, "The Pecking Order, Debt Capacity, and Information Asymmetry," *Journal of Financial Economics*, 95, 332–355.

Ljungqvist, A., F. Marston, and W. Wilhelm, 2006, "Competing for Securities Underwriting Mandates: Banking relationships and Analyst Recommendations," *Journal of Finance*, 61, 301–340.

Lummer, S. L., and J. J. McConnell, 1989, "Further evidence on the bank lending process and the capital-market response to bank loan agreements," *Journal of Financial Economics*, 25(1), 99–122.

Mason, J. K. M., 1990, "Do taxes affect corporate financing decisions?," *Journal of Finance*, 45(5), 1471–1493.

Michaely, R., and M. R. Roberts, 2007, "Corporate Dividend Policies: Lessons from Private Companies," *Working Paper*.

Norden, L., and W. Wagner, 2008, "Credit derivatives and loan pricing," *Journal of Banking and Finance*, 32, 2560–2569.

Rajan, R., 1992, "Insiders and Outsiders: The Choice Between Informed and Arm's Length Debt," *The Journal of Finance*, 47(4).

Roberts, M. R., and A. Sufi, 2009, "Renegotiation of financial contracts: Evidence from private credit agreements," *Journal of Financial Economics*, 93, 159–184.

Rosenbaum, P. R., and D. B. Rubin, 1983, "The Central Role of the Propensity Score in Observational Studies for Causal Effects," *Biometrika*, 70, 41–55.

Rubin, D. B., and N. Thomas, 2000, "Combining Propensity Score Matching with Additional Adjustments for Progostic Covariates," *Journal of the American Statistical Association*, 95(450), 573–585.

Santos, J. A. C., and A. Winton, 2008, "Bank Loans, Bonds, and Information Monopolies across the Business Cycle," *Journal of Finance*, 63(3).

Schenone, C., 2010, "Lending Relationships and Information Rents: Do Banks Exploit Their Information Advantages?," *Review of Financial Studies (forthcoming)*.

Sharpe, S. A., 1990, "Asymmetric Information, Bank Lending and Implicit Contracts: A Stylized Model of Customer Relationships," *Journal of Finance*, 45, 1069–1087.

Smith, J., and P. Todd, 2005, "Does Matching Overcome LaLonde's Critique of Nonexerimental Estimators?," *Journal of Econometrics*, 125(1-2), 305–353.

Song, M. H., and R. A. Walkling, 1993, "The Impact of Managerial Ownership on Acquisition Attempts and Target Shareholder Wealth," *Journal of Financial and Quantitative Analysis*, 28(4), 439–457.

Sufi, A., 2007, "Information Asymmetry and Financing Arrangements: Evidence from Syndicated Loans," *The Journal of Finance*, 62(2), 629–668.

Wittenberg-Moerman, R., 2005, "The Role of Information Asymmetry and Financial Reporting Quality in Debt Contracting: Evidence from the Secondary Loan Market," *Working Paper*.

Wright, P., S. P. Ferris, A. Sarin, and V. Awasthi, 1996, "Impact of Corporate Insider, Blockholder, and Institutional Equity Ownership on Firm Risk Taking," *Academy of Management Journal*, 39(2), 441–463.

Appendix Table 1
Endogeneity: Propensity Score Matching

The dependent variable is PUBLIC, a dummy variable equal to 1 if the firm is public. Borrower characteristics include the log of borrower size, interest coverage, leverage, tangibility, a dummy whether the borrower is investment grade or not rated, profitability, growth, cash, assets and age. Loan characteristics include the log of loan size, maturity, dummy variables for loan type, loan purpose, refinancing, secured and covenants (all variables are defined in Appendix Table 10). Other control variables include 1 digit SIC codes as well as time fixed effects. We use 3 matching methods, Nearest Neighbor Matching with 50 and 100 neighbors and Local Linear Matching using a Gaussian Kernel. Panel A reports the results matching private and public firms on the basis of propensity scores with nearest neighbor matching. The nearest neighbor estimator chooses for each public loan the 100 (NN 100) or 50 (NN 50) private loans with closest propensity scores and uses the arithmetic averages of AISD for these private loans. Panel B reports the results matching private and public firms on the basis of propensity scores with local linear matching matching. Standard errors are calculated by bootstrapping with 50 (BS 50), 100 (BS 100) and 300 (BS 300) replications. We also report standard errors without bootstrapping.

	Procedure	Coefficient	(Std. Error)
Panel A: Nearest Neighbor Matching			
NN 50	BS 50	-26***	(7.923)
	BS 100	-26***	(6.887)
	BS 300	-26***	(8.214)
	w/o BS	-26***	(8.591)
NN 100	BS 50	-46***	(10.255)
	BS 100	-46***	(8.037)
	BS 300	-46***	(9.217)
	w/o BS	-46***	(7.986)
Panel B: Local Linear Matching			
Gaussian	BS 50	-60***	(8.043)
	BS 100	-60***	(8.219)
	BS 300	-60***	(9.121)
	w/o BS	-60***	(8.266)

Significance levels : $*$: 10% $**$: 5% $***$: 1%

Appendix Table 2
Bond Market Access

This table reports the results for the impact of the cost of information production on loan spreads for private versus public firms. It presents alternative proxies to characterize the information availability of private versus public firms. The dependent variable is the All-In-Spread-Drawn (AISD). This table only reports the coefficient estimates for the main explanatory variables. The regressions further include all other control variables used in the previous analyses: *borrower credit risk, loan contract terms, loan purpose control variables as well as time and industry dummies*. Panel B reports the results for the impact of bond market access on loan spreads for private versus public firms. Bonds is a dummy variable equal to one if the firm has issued public debt in the past. Last Bond Public is a dummy variable equal to one if the last bond of the firm has been a public bond. Log(1+Prior Public Bonds) is the natural logarithm of one plus the number of bonds issued by the borrower prior to loan origination. Log(1+Prior Public Bonds) is the natural logarithm of one plus the number of public bonds issued by the borrower prior to loan origination.

Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Public	-26.96***	-27.185***	-27.254***	-34.213***	-32.084***	-31.542***	
	(4.718)	(4.740)	(4.742)	(5.215)	(5.087)	(5.046)	
(1) Bonds	-7.768			-45.736***			
	(5.373)			(8.398)			
(2) Last Bond Public		-3.474			-38.655***		
		(5.604)			(19.179)		
(3) Log(1+Prior Bonds)			-2.369			-19.629***	
			(3.471)			(5.654)	
(4) Public x Bonds				46.453***			
				(9.051)			
(5) Public x Last Bond Public					42.128***		
					(10.032)		
(6) Public x Log(1+Prior Bonds)						19.173***	
						(4.828)	
Public x No Bond							0.565
							(7.942)
Private x Bonds							-11.953
							(9.349)
Private x No Bonds							34.117***
							(6.711)
Borrower Characteristics	YES	YES	YES	YES	YES	YES	YES
Loan Characteristics	YES	YES	YES	YES	YES	YES	YES
Loan Purpose Control	YES	YES	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES	YES	YES
Industry Fixed Effects	YES	YES	YES	YES	YES	YES	YES
Diagnostics							
Wald-Test: |(1)|=|(4)| [p-value]				0.901			
Wald-Test: |(2)|=|(5)| [p-value]					0.564		
Wald-Test: |(3)|=|(6)| [p-value]						0.894	
Number Obs.	1,764	1,764	1,764	1,764	1,764	1,764	1,764
R^2	0.602	0.601	0.606	0.609	0.608	0.607	0.605

Significance levels : $*$: 10% $**$: 5% $***$: 1%

Appendix Table 3
Exchange Listings

Due to data limitations, we run tests for (i) and (iii) using a subset of public firms where (historic) information about segment affiliation and index membership is available. Panel A shows descriptive statistics (borrower total assets (Total Assets), loan spread (AISD), the number of shareholders (Owner) and loan tenor (Tenor)) for firms within the different trading segments on the Main Market (FTSE 100, FTSE 250, Small Cap, Other) and the Alternative Investment Market (AIM). We also include the descriptive statistics for private firms. Panel B reports the regression results. Columns (1) and (2) show the results using segment affiliation as information proxy. FTSE 100/FTSE 250 is a dummy variable equal to one if the firm's equity is traded on these two segments. Small Cap/Other/AIM is a dummy variable equal to one if the firm's equity is traded on these segments. Column (1) shows results only for public firms.Standard errors (shown in parentheses) are heteroscedasticity robust, clustered at the firm level.

Panel A: Descriptive statistics of trading segments

Segment	Total Assets ($ millions)	AISD (bps)	Owner (Number)	Tenor (years)
1. Public Firms				
Main Market				
FTSE 100	14,212	98	59	3.66
FTSE 250	2,029	101	57	3.73
Small Cap	621	177	31	4.03
Other	605	162	34	3.92
AIM				
AIM	175	142	19	4.09
2. Private Firms				
Bonds	4,068	120	2	3.73
No Bonds	969	244	2	4.34

Panel B: Regression analysis

Variable	(1)	(2)	(3)
FTSE 100/FTSE 250	-32.328***	-39.028***	
	(11.263)	(7.113)	
Small Cap / AIM		-16.410	29.678***
		(9.972)	(10.133)
Private x Bonds			2.924
			(7.812)
Private x No Bonds			61.911***
			(7.641)
Borrower Characteristics	YES	YES	YES
Loan Characteristics	YES	YES	YES
Loan Purpose Control	YES	YES	YES
Year Fixed Effects	YES	YES	YES
Industry Fixed Effects	YES	YES	YES
Diagnostics			
N	403	1,240	1,240
R^2	0.694	0.601	0.621

Significance levels : $*$: 10% $**$: 5% $***$: 1%

Appendix Table 4
Bargaining Power

This table reports the results for the impact of relationships on loan spreads for private versus public firms. The dependent variable is the All-In-Spread-Drawn (AISD). This table only reports the coefficient estimates for the main explanatory variables. The regressions further include all other control variables used in the previous analyses: *borrower credit risk, loan contract terms, loan purpose control variables as well as time and industry dummies*. Private is a dummy variable equal to one if the firm is not stock exchange listed. Rel(Dummy) is a a dummy variable equal to one if the borrower had a relationship with the lead bank in the previous 5 years of borrowing history of the firm. Rel(Number) measures the strength of the relationship based on the number of loans by the lead bank to the borrower relative to the total number of loans by this borrower in the last 5 years. Rel(Amount) measures the strength of the relationship based on the amount of loans by the lead bank to the borrower relative to the total amount of loans by this borrower in the last 5 years. Bonds is a dummy variable equal to one if the borrower has issued public bonds in the past. Standard errors (shown in parentheses) are heteroscedasticity robust, clustered at the firm level.

Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Public	-27.349***	-27.065***	-27.233***	-18.954***	-20.845***	-19.952***	
	(4.777)	(4.772)	(4.769)	(5.558)	(5.541)	(5.521)	
Private							24.058***
							(5.922)
(1) Rel(Dummy)	8.119**			21.965***			-5.313
	(4.074)			(6.512)			(6.025)
(2) Rel(Number)		15.597**			33.291***		
		(6.416)			(10.464)		
(3) Rel(Amount)			11.297*			32.265***	
			(6.322)			(10.524)	
(4) Rel(Dummy) x Public				-23.682***			
				(7.925)			
(5) Rel(Number) x Public					-30.337**		
					(12.716)		
(6) Rel(Amount) x Public						-35.111***	
						(12.640)	
Bonds							1.180
							(9.274)
Rel(Dummy) x Bonds							2.035
							(10.972)
Rel(Dummy) x Private							31.280***
							(8.932)
Bonds x Private							-35.990***
							(13.435)
Rel(Dummy) x Private x Bonds							-37.190**
							(18.123)
Borrower Characteristics	YES	YES	YES	YES	YES	YES	YES
Loan Characteristics	YES	YES	YES	YES	YES	YES	YES
Loan Purpose Control	YES	YES	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES	YES	YES
Industry Fixed Effects	YES	YES	YES	YES	YES	YES	YES
Diagnostics							
Wald-Test: |(1)|=|(4)| [p-value]				0.729			
Wald-Test: |(2)|=|(5)| [p-value]					0.703		
Wald-Test: |(3)|=|(6)| [p-value]						0.707	
N	1,764	1,764	1,764	1,764	1,764	1,764	1,764
R^2	0.602	0.607	0.606	0.604	0.608	0.608	0.613

Significance levels : $*$: 10% $**$: 5% $***$: 1%

Appendix Table 5
Ownership Structure

This table reports results for the impact of ownership structure on loan spreads. Panel A analyzes how insider ownership affects loan spreads.The dependent variable is the All-In-Spread-Drawn (AISD). This table only reports the coefficient estimates for the main explanatory variables. The regressions further include all other control variables used in the previous analyses: *borrower credit risk, loan contract terms, loan purpose control variables as well as time and industry dummies.* Owners denotes the number of shareholders of the borrower. Columns (1) to (3) report the results using the number of owners as proxy of insider ownership. Column (1) reports the results for the full sample. Columns (2) and (3) show the impact of ownership in the subsample of public and private firms, respectively.

	Insider Ownership				**Private Equity Ownership**	
		Private	Public			
Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
(1) Public	-21.089***				-24.154***	-26.112***
	(8.103)				(5.308)	(5.205)
Log(Owners)	-7.903***	-4.309	-5.120***			
	(1.985)	(6.450)	(1.895)			
(2) Public x HHI (Low)				-44.343***		
				(7.370)		
(3) Public x HHI (High)				-25.851***		
				(8.616)		
PtP					84.731***	
					(9.801)	
LBO/MBO					55.408***	
					(8.561)	
Private Equity (Not Buyout)					82.714***	
					(9.173)	
Private Equity						65.689***
						(7.059)
(4) Public x Private Equity						26.678***
						(9.389)
Borrower Characteristics	YES	YES	YES	YES	YES	YES
Loan Characteristics	YES	YES	YES	YES	YES	YES
Loan Purpose Control	YES	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES	YES
Industry Fixed Effects	YES	YES	YES	YES	YES	YES
Diagnostics						
Wald-Test: |(2)|=|(3)| [p-value]				0.009		
Wald-Test: |(1)|=|(4)| [p-value]						0.945
N	1,063	503	560	1,059	1,764	1,764
R^2	0.605	0.427	0.674	0.602	0.639	0.638

Significance levels : $*$: 10% $**$: 5% $***$: 1%

Appendix Table 6
Secondary Market Trading

This table reports results assessing the impact of loan liquidity on loan spreads. Panel A shows the calender time distribution of liquid versus illiquid loans for our full sample, and private and public cohorts, respectively. Panel B shows the regression results. The dependent variable is the All-In-Spread-Drawn (AISD). This table only reports the coefficient estimates for the main explanatory variables. The regressions further include all other control variables used in the previous analyses: *borrower credit risk, loan contract terms, loan purpose control variables as well as time and industry dummies.* Traded (Not Traded) is a dummy variable equal to 1 if the loan has (not) been traded in the secondary market after origination. Public is a dummy variable equal to 1 if the firm is stock exchange listed. Standard errors (shown in parentheses) are heteroscedasticity robust, clustered at the firm level.

Panel A: Distribution of traded vs. not traded loans for private and public companies

	Full Sample			**Private Firms**			**Public Firms**		
Year	**Not Traded**	**Traded**	**Total**	**Not Traded**	**Traded**	**Total**	**Not Traded**	**Traded**	**Total**
1989 - 1998	163	0	163	27	0	27	136	0	136
...									
1999	113	2	115	33	2	35	80	0	80
2000	168	6	174	47	0	47	121	6	127
2001	131	3	134	35	1	36	96	2	98
2002	121	14	135	41	4	45	80	10	90
2003	124	23	147	46	5	51	78	18	96
2004	163	45	208	91	24	115	72	21	93
2005	233	23	256	154	17	171	79	6	85
2006	224	54	278	153	43	196	71	11	82
2007	218	14	232	141	13	154	77	1	78
Total	**1,658**	**184**	**1,842**	**768**	**109**	**877**	**890**	**75**	**965**

Panel B: Regression results

Variable	**(1)**	**(2)**
Public	-25.328***	-21.796***
	(4.756)	(4.915)
(1) Traded	30.860***	45.186***
	(6.873)	(9.148)
(2) Public x Traded		-34.213***
		(12.902)
Borrower Characteristics	YES	YES
Loan Characteristics	YES	YES
Loan Purpose Control	YES	YES
Year Fixed Effects	YES	YES
Industry Fixed Effects	YES	YES
Diagnostics		
Wald-Test: (1)=|(2)| [p-value]		0.252
N	1,764	1,764
R^2	0.607	0.608

Significance levels : $*$: 10% $**$: 5% $***$: 1%

Appendix Table 7
Future Performance

This table reports the results for the impact of being public on loan spreads. The dependent variable is the All-In-Spread-Drawn (AISD). Sales Growtht+1 is the sales growth over a one year period in the future, Z-Score$_{t+1}$ is the change in the Altman Z-Score over a one year period, respectively. The other variables are defined accordingly. The regressions further include all other control variables used in the previous analyses: borrower credit risk, loan contract terms, loan purpose control variables as well as time and industry dummies (see Table 4 for a definition of these variables). Standard errors (given in parentheses) are heteroscedasticity robust, clustered at the borrowing firm.

Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Public	-42.078***	-42.401***	-34.414***	-43.595***	-43.627***	-36.568***
	(7.683)	(9.121)	(9.403)	(7.883)	(9.299)	(9.463)
Sales Growth$_{t+1}$	0.0001			-0.004		
	(0.001)			(0.003)		
Sales Growth$_{t+2}$		0.0001			-0.001	
		(0.001)			(0.001)	
Sales Growth$_{t+3}$			-.00002			-0.005*
			(0.001)			(0.003)
Public x Sales Growth$_{t+1}$				0.005		
				(0.003)		
Public x Sales Growth$_{t+2}$					0.001	
					(0.001)	
Public x Sales Growth$_{t+3}$						0.006*
						(0.003)
Borrower Characteristics	YES	YES	YES	YES	YES	YES
Loan Characteristics	YES	YES	YES	YES	YES	YES
Loan Purpose Control	YES	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES	YES
Industry Fixed Effects	YES	YES	YES	YES	YES	YES
Diagnostics						
N	928	722	533	928	722	533
R^2	0.626	0.627	0.6	0.627	0.627	0.598

Significance levels : $*$: 10% $**$: 5% $***$: 1%

Appendix Table 8
Predicting the Default Risk of Private and Public Firms

Panel A: Z-Score in the Literature

Panel A provides a brief overview of recent papers in the finance literature that used either of the predictors of default.

	Z-Score Method	**Used In**
1	Altman Z-Score (Z)	Acharya, Bharath, and Srinivasan (2007)
		Bradley and Roberts (2003)
		Hillegeist, Keating, Cram, and Lundstedt (2004)
		Eisdorfer (2008)
		Roberts and Sufi (2009)
2	Z'-Score (Z')	
3	Modified Z-Score (Z_M)	Mason (1990)
		Graham, Lemmon, and Schallheim (1998)
		Acharya, Bharath, and Srinivasan (2007)
		Leary and Roberts (2010)
4	Zmijewski Score (Z_{ZMI})	Acharya, Bharath, and Srinivasan (2007)
5	Ohlson O-Score (O)	Dichev (1998)
		Hillegeist, Keating, Cram, and Lundstedt (2004)

Panel B: Correlations (Public Firms)

Panel B reports the correlation between the individual predictors of default in the subsample of public firms. Z is the Altman Z-Score, Z' the private firm Z-Score (Altman (2000)), Z_M the modified (MacKie-Mason) Z-Score, Z_{ZMI} the Zmijewski Score and O the Ohlson O Score. P-values are reported in parentheses.

	Z	Z'	Z_M	Z_{ZMI}	O
Z	1				
Z'	0.6512	1			
	(0.000)				
Z_M	0.4848	0.7939	1		
	(0.000)	(0.000)			
Z_{ZMI}	-0.3197	-0.2172	-0.8339	1	
	(0.000)	(0.000)	(0.000)		
O	-0.3817	-0.2066	-0.1377	0.5583	1
	(0.000)	(0.000)	(0.000)	(0.000)	

(continued on next page)

Panel C: Summary Statistics (Default Predictors)

Panel C reports summary statistics for the various default predictors. *Z'* is the private firm Z-Score (Altman (2000)), Z_M the modified (MacKie-Mason) Z-Score, Z_{ZMI} the Zmijewski Score and O the Ohlson O Score. Obs. is the number of firm-year observations.

	Obs.	Mean	Std. Dev.	Min.	Max.
Z'	3,367	1.586	0.884	0.293	3.573
Z_M	3,447	1.360	0.902	0.077	3.423
Z_{ZMI}	3,150	-0.954	1.465	-3.287	2.222
O	3,069	0.811	1.557	-1.900	3.551

Panel D: Correlations (Full Sample)

Panel D reports the correlation between the individual predictors of default in the subsample of public firms. *Z'* is the private firm Z-Score (Altman (2000)), Z_M the modified (MacKie-Mason) Z-Score, Z_{ZMI} the Zmijewski Score and O the Ohlson O Score. P-values are reported in parentheses.

	Z'	Z_M	Z_{ZMI}	O
Z'	1			
Z_M	0.9338	1		
	(0.000)			
Z_{ZMI}	-0.2319	-0.063	1	
	(0.000)	(0.000)		
O	-0.2738	-0.103	0.81	1
	(0.000)	(0.000)	(0.000)	

Appendix Table 9
Ex-Post Performance of Private versus Public Firms

Panel A of Appendix Table 9 reports ex-post changes in various proxies for borrower credit quality. We use Z', Z_M the modified (MacKie-Mason) Z-Score, Z_{ZMI} the Zmijewski Score and O the Ohlson O Score. t+1, t+2 and t+3 are ex-post changes 1, 2 and 3 years after loan origination, respectively. The dependent variables are changes in the different Z-Score measures. This table only reports the coefficient estimates for PUBLIC. Panel B reports the ex-post changes in sales growth for private versus public firms in year 1, 2 and 3 after loan origination. The regressions further include all other control variables used in the previous analyses: *borrower credit risk, loan contract terms, loan purpose control variables as well as time and industry dummies.* Standard errors (given in parentheses) are heteroscedasticity robust, clustered at the borrowing firm. Panel C reports the cross-sectional test of cumulative abnormal returns (CAR) of public firm loans.

Panel A: Ex-post change in Z-Score

Dependent Variable	**(1) t+1**	**(2) t+2**	**(3) t+3**
Z'	-0.077	-0.126	-0.154
	(0.0752)	(0.0831)	(0.1068)
N	922	725	531
R^2	7.43	10.05	20.05
Z_M	-0.049	-0.069	-0.081
	(0.069)	(0.073)	(0.126)
N	958	751	549
R^2	6.77	12.15	22.26
Z_{ZMI}	0.187	0.21	0.54
	(0.156)	(0.147)	(0.189)
N	824	658	508
R^2	10.43	13.38	22.97
O	0.137	0.371^{*}	0.297
	(0.161)	(0.181)	(0.188)
N	909	711	510
R^2	8.63	17.99	14.27

Significance levels : † : 10% $*$: 5% $**$: 1%

Panel B: Ex-post change in sales growth

Variable	**(1) t+1**	**(2) t+2**	**(3) t+3**
Public	-0.073	0.130	0.363
	(0.111)	(0.130)	(0.371)
N	928	722	533
R^2	19.73	25.17	30.21

Significance levels : † : 10% $*$: 5% $**$: 1%

(continued on next page)

Panel C: Performance of public and private firm loans in the secondary loan market

CAR for public loan i is defined as

$$CAR_i \equiv \sum_{t=1}^{T}(R_{public,t} - R_{matched-private(i),t})$$

Variable	1 year CAR
N	48
Mean	$-0.0045^{\dagger}$
S.E.	0.0023
t-value	-1.94

Significance levels : † : 10%

Appendix Table 10
Variable Definition

Variable	Definition
Dependent Variable	
AISD	Is the all-in-spread-drawn, which is the spread plus annualized upfront fees above LIBOR.
Instrument	
log(1+distance)	Natural logarithm of 1 plus the distance from the firm's headquarter to London.
Inference Variables	
Public	Dummy equal to one if the firm is public.
Bonds	Dummy equal to one if firm has issued public bond in the past.
Last Bond Public	Dummy equal to one if the last bond issued was a public bond.
Log(1+Prior Bonds)	Natural logarithm of 1 plus the number of public bonds issued before the loan origination date.
No Bonds	Dummy equal to one if the firm has not issued a public bond in the past.
FTSE100 / FTSE250	Dummy variable equal to one if firm is traded as part of these two indices.
Small Cap / AIM	Dummy variable equal to one if firm is traded as part of these two indices.
Rel(Dummy)	Dummy variable equal to one if current lead arranger has been lead arranger of a loan to the same firm in the 5 years prior to the current loan.
Rel(Number)	Ratio of the number of loans extended by the lead arranger to the same borrower as a percentage of the total number of loans this borrower received in the 5 past years prior to the current loan.
Rel(Amount)	Ratio of the $ amount of loans extended by the lead arranger to the same borrower as a percentage of the total $ amount of loans this borrower received in the 5 past years prior to the current loan.
Log(Owners)	Natural logarithm of the number of reported shareholders.
HHI(Low)	We calculate the Herfindahl-Hirschman-Index (HHI) with the percentage ownership share of each reported shareholder. HHI(Low) is a dummy variable equal to one if ownership concentration is low, i.e. below 0.67
HHI(High)	Dummy variable equal to one if ownership concentration is high, i.e. above 0.67.
PtP	Dummy equal to one if deal is a public-to-private transaction.
LBO/MBO	Dummy equal to one if deal is a LBO or MBO (but not a PtP)
Private Equity (No Buyout)	Dummy equal to one if deal involves a private equity sponsor but is not a buyout.
Private Equity	Dummy equal to one if deal involves a private equity sponsor.
Traded	Dummy equal to one if loan has been traded on the secondary market after origination.
Sales Growth$_{t+i}$	Sales growth rate of firm i years after loan origination (i$\in [1,2,3]$)

(continued on next page)

Control Variables	
Borrower Characteristics	
Profitability	Ratio of EBITDA to Sales
Growth	Sales growth ($\text{Sales}_t/\text{Sales}_{t-1}$)
Leverage	Ratio of long term debt over total assets.
Log(Cash)	The natural logarithm of cash & equivalents.
Log(Assets)	The natural logarithm of total assets.
Log(Age)	The natural logarithm of one plus the age of the company measured in months.
Tangible	Ratio of tangible fixed assets over total assets.
Log(1+Interest Coverage)	Measured as the natural logarithm of one plus EBITDA / interest paid.
Investment Grade	Dummy variable equal to one if the borrower is investment grade rated.
Not Rated	Dummy variable equal to one if the borrower is not rated.
Loan Characteristics	
Term Loan	Dummy variable equal to one if loan is term loan.
Log(1+Maturity)	Measured as the natural logarithm of one plus loan maturity (measured in months).
Log(Loan Size)	Measured as the natural logarithm of one plus the loan facility amount.
Covenants	Dummy variable equal to one if loan contract specifies covenants.
Secured	Dummy variable equal to one if loan is secured with collateral.
Secured Missing	Dummy variable equal to one if loan secured status is missing.
Refinancing	Dummy variable equal to one if loan is refinancing loan.
Loan Purpose	Separate dummy variables for corporate structure, capital structure, acquisition and project finance purposes.