Nimble banks

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June 24, 2026

Abstract

We examine how organizational flexibility influences investment decisions. We develop a novel measure of decentralized decision-making based on observed differences in the pricing of loans across subsidiaries of a banking group. We find that decentralized banks earn economically meaningful higher spreads on loans to borrowers with comparable characteristics. We provide evidence that this can be explained by them better exploiting lending opportunities arising from high, and urgent, demand. They do so by being more flexible in terms of the industries and countries they lend to, and by reacting more quickly to changes in aggregate lending conditions. Overall, the results suggest that a decentralized organization yields material benefits by facilitating more flexible decision-making.

JEL Classification: D23, L23, G2

Keywords: Decentralization, flexibility, lending

*We thank participants at seminars at Columbia University, Hong Kong University, University of Bologna and at the Finance in the Tuscan Hills workshop for comments. Wouter Dessein is at Columbia University, email: wd2179@gsb.columbia.edu, Bálint Horváth is at the University of Arizona, email: horvathb@arizona.edu, Wolf Wagner is at Erasmus University Rotterdam, email: wagner@rsm.nl, Wei Zhai is at the Central University of Finance and Economics, email: wei.zhai@cufe.edu.cn.

1 Introduction

We show a novel benefit to operating firms in a decentralized way: flexibility. The latter permits undertaking more profitable investments by being able to pursue a larger set of opportunities, and by reacting to them faster.

We investigate investment decisions in the banking industry, which offers two advantages. First, the vast majority of large banks operate through a web of global subsidiaries, making the question of whether or not to decentralize very relevant. Second, banks compete globally on a single "product" (making loans) and this product and its pricing (the interest rate) are fairly standardized.

We first introduce a framework that shows how decentralization enables flexibility, and that there is a trade-off with organizational costs. We consider an environment with a limited number of (highly) profitable lending opportunities that appear unpredictably. We think of those as driven by temporary, possibly urgent, funding demands by firms that allow banks to charge higher rates. There are also (very) unprofitable projects that can be mistaken for other projects. Centrally-operated banks can avoid those projects by imposing hard requirements on which projects can be undertaken or by requiring central approval. The downside to a hard requirement is that a bank may not be able to capitalize on a profitable opportunity (as that opportunity may not meet the hard criteria) and finance an average project instead. The bank may also miss out on opportunities that are only available temporarily due to delay caused by central approval. Decentralized banks have full flexibility in their project choice, implying that in principle they can pursue all opportunities. However, in order to avoid that they mistakenly choose the unprofitable project, they require better training and higher skills, which comes at a cost.

The framework yields several predictions. First, decentralized banks earn (in expectation) higher interest rates (conditional on project characteristics). Second, they are more likely to lend when a borrower has high and urgent demand. Third, they pursue a wider set of opportunities and react faster to common information, that is, they act more flexibly.

To test these predictions, we develop a novel measure of decentralized decision-making. Unlike measures of decentralization used in prior literature (which are predominantly based on formal authority), it is derived from *actual* decisions.[1] Specifically, a firm is deemed to be centralized when its subsidiaries make *similar* decisions when presented with *similar* investment opportunities. In the context of banks, centralization can take the form of a central loan approval system, or the requirement for certain loans (for example, exceeding a size threshold) to be approved by the parent. In either case, centrally-run operations should result in more similar decisions across different entities of a bank.

Following prior literature (e.g., Santos (2010)), we measure decisions through the pricing of loans. We use for this the market for syndicated loans. This market operates world-wide, and most large corporates and large banks participate in it. We have data on individual lending decisions in this market, allowing to control for "project" characteristics. An important feature of the market, for our purposes, is that a syndicate typically consists of different types of banks, passive ones, and active ones that also set pricing, which allows to differentiate the decision to join a syndicate from the pricing decision.

Decentralization is then measured by the extent to which a bank's subsidiaries deviate *differently* from the global pricing of a loan. For example, a banking group with subsidiaries that all charge 10 bps higher rates is deemed to be centrally run, whereas a group that has some subsidiaries charging the global rate and others 20 bps more is deemed to be decentralized. Formally, a group's decentralization measure is constructed from all subsidiary-pairs of the group across all loans they originate over a given time period. We verify that the measure has informational content by showing that it is related to survey-based measure of lending decentralization.

We then examine the three predictions. We first investigate whether when a decentralized bank participates in a syndicate, interest rates are higher. Controlling for a wide set of borrower and loan-factors (such as leverage or loan collateralization) we find this to be the case. The effect is economically large: A one standard deviation increase in decentral-

[1] Formal and real authority may differ for several reasons (Aghion and Tirole, 1997). For instance, a superior with formal power may in practice just rubber stamp decisions of a subordinate.

ization is associated with 19 bps increase in the loan spread, about 12% of the mean. This suggests that decentralization affords banks material benefits (this does not imply though that decentralized banks are necessarily more profitable since a decentralized structure is also more costly to operate). The result is robust to a wide set of specifications. It also continues to hold when we generate exogenous variation in decentralization using bank mergers.

Second, our framework predicts that the rate benefit arises due to decentralized banks better taking advantage of opportunities arising from borrower demand. Consistent with this we find that when a borrower has high demand, decentralized banks are more likely to lend to that borrower. There is also evidence that these banks lend more when there is urgent demand, as proxied by funding of a leveraged buyout (LBO). Conversely, the results disappear (in terms of economic magnitude) when we control for demand by using borrower-year fixed effects. Third, we provide evidence that decentralized banks lend more flexibly: they are less bound to specific industries and countries when pursuing a new opportunity. Also, they react first to aggregate changes in lending conditions, as proxied by the beginning of a credit cycle in the borrower country.

We distinguish our channel from several alternative explanations, in particular the presence of *soft information* and *subsidiary heterogeneity*. Subsidiaries of a group may have different endowments with soft information, which may result in them pricing loans differently unrelated to decentralization. The potential for soft information is somewhat limited from the outset in our setting (the borrowers in the syndicated loan market are large firms for which information tends to be readily available) and we carry out tests that more directly exclude soft information. Most importantly, our results also hold when we create the decentralization measure exclusively using differences in the pricing of *observeable* borrower characteristics. An informational explanation is also inconsistent with decentralized banks reacting differently to *observeable* changes in borrower demand and *aggregate* lending conditions, as well as with them being less specialized in terms of industries and countries. Subsidiaries may also be subject to heterogeneous external conditions, resulting in different hurdle rates. For example, when the internal capital market of a bank works only imperfectly, subsidiaries with a scarcity of capital may demand an extra compensation for lending. Again, this may create dispersion across subsidiaries unrelated to decentralization. Our results seem inconsistent with that channel as they are also present when we control for individual subsidiaries having different hurdle rates in each period.

The empirical literature on decentralization (both for firms and banks) has emphasized that benefits to decentralization arise because of better information (either about borrowers, in the form of soft or private information, or about local economic conditions) and because of better usage a such information, allowing for example a better reaction when local circumstances change. Our paper shows a novel benefit to decentralization: the ability to consider a larger set of opportunities. This benefit is neither driven by better information, nor by being better able to response to local shocks.

Analyzing firms, Acemoglu, Aghion, Lelarge, Van Reenen, and Zilibotti (2007) have shown the importance of non-public information: Firms that are young, are closer to the technology frontier, or operate in heterogeneous environments, are more likely to be decentralized. Huang, Li, Ma, and Xu (2017) show that when the distance to the government is farther, SOE's in China are more likely to be decentralized. Aghion, Bloom, Lucking, Sadun, and Van Reenen (2021) find that firms that delegated more power to local plant managers prior to Great Recession outperformed centralized counterparts in sectors that were hardest hit by the subsequent crisis. Bandiera, Best, Khan, and Prat (2021) analyze the consequences of autonomy of procurement officers in Pakistan, and find that autonomy reduces procurement prices with no quality reductions. Kala (2024) studies a policy reform in India where managers of SOE are granted more autonomy, and finds that this increases spending on labor and capital, resulting in greater value added.

A number of studies have also analyzed the organizational structure of banks specifically, again emphasizing informational aspects. Closely related to this point, Liberti and Mian (2009) show that greater hierarchical/geographical distance between the information collecting agent and the loan approving officer leads to less reliance on subjective information. Canales and Nanda (2012) introduce a survey-based measure of decentralization, finding that decentralized banks give larger loans to small firms and firms with soft information. Skrastins and Vig (2019) show that increasing the number of managerial layers within a bank branch induces credit rationing, reduces loan performance, and generates standardization in loan contracts. Dlugosz, Gam, Gopalan, and Skrastins (2024) introduce a novel measure of bank organizational structure based on where branch deposit rates are set. They document the effect of delegation on deposits and on the banks' ability to react to local shocks (e.g. mortgage lending).

The remainder of the paper is organized as follows. The next section introduces a framework for banks operating decentrally or centrally, showing that banks that decide to be decentralized can pursue a larger set of lending opportunities. The section also derive a set of empirical predictions. Section 3 introduces our measure of decentralization and Section 4 the data. Section 5 shows that the measure correlates with survey evidence of lending decentralization, but not other dimensions of decentralization. Section 6 examines the lending behaviour of decentralized banks, examining the various predictions.

2 Decentralization and lending opportunities: A framework

There are two dates (0 and 1) and two (regular) projects. Projects require one unit of funds at date 0 and normally return 1 at date 1. However, one of the two projects (with equal likelihood) will be in the high state at date 0, meaning that it will return $1 + r$ ($r > 0$) at date 1. We interpret this as high demand for funds by a borrower, and hence a higher willingness to pay for a loan. For each regular project, there is also a corresponding bad project that returns 0 at date 1. One of the two regular projects (again with equal likelihood) has an identifiable characteristic that is commonly observed at date 0 and distinguishes it from its bad project.

Screening. A (local) bank manager screens projects at date 0. In the process of doing so, the manager learns which of the two regular projects is in the high state. If a cost c is incurred, the manager can also separate regular projects from bad projects, regardless of the identifiable characteristic. The cost has to be incurred before screening. It can be seen as expenses associated with hiring a skilled manager, or training her. Alternatively, it can also represent the cost of avoiding agency problems. For example, a remuneration scheme for the manager to avoid that the bad project is chosen, in case the latter provides private benefits to the manager.

Organizational Structure. A bank can finance one project, and can be run in two ways. First, it can require its local manager to select only a project with the identifiable characteristic, which we view as centralization. This can be given several interpretations:

1. The bank runs a centralized approval system that allows only projects with specific characteristics to be funded. For example, the bank may require a project to have an existing external assessment (e.g., a corporate governance rating), to be sufficiently transparent, or to be in an industry that the bank has expertise in (to avoid that the project is mistaken for a bad project).

2. In the absence of the cost c, only the center can distinguish regular from bad projects. The identifiable characteristic may then indicate a project with limited urgency, allowing for time for the local manager to relay information to the central manager and for the latter to approve it. In this case, the local manager would send the slow project and its corresponding bad project for review.

3. Similarly, only projects of limited complexity may be funded. This may be because review of a complex project by the central manager takes too much time (and hence the opportunity vanishes) or because the central manager does not find it worthwhile its time to review complex projects. In this case, the local manager would send the simple project and its corresponding bad project for review.

4. Finally, preparing a project for review may be costly to the local manager and involve a lengthy process. A project with the identifiable characteristic is always approved, whereas those without it are only approved with a 50% probability. If rejected, there may be limited time for implementing a new project (and the preparation cost has to be incurred again). Local managers may therefore not find it

worthwhile to send such a project for review.

Second, the bank can give the (local) manager full discretion, in combination with incurring the cost c. We interpret this as decentralization.[2]

This leads to a simple trade-off determining the optimal organizational form. A centralized bank can capitalize on the high-return project with a likelihood of 50% (occurring when the high-return project has the identifiable characteristic). Its expected (net) return from lending is hence $\frac{r}{2}$. The expected net return for a decentralized bank is r instead as it can always make use of the high-return project.[3] Thus, if

$$\frac{r}{2} > c, \tag{1}$$

the bank (strictly) benefits from being decentralized. Note that under either organizational form the bank undertakes the regular project; the organizational form only determines how the bank avoids bad projects (a centralized bank through limiting project choice, and a decentralized one through skilled staff).

Equilibrium: The above considers the decision of a single bank, taking the project return (the "interest rate") r as given. Consider now a local lending market inhabited by a mass 1 of banks. Assume that the (excess) return r is declining in the mass of banks selecting the high-return project (this is reduced form for imperfect competition in the project market, see for example Salop (1979)): $r = r(\cdot)$ with $r'(\cdot) < 0$. Denote with $d \in [0, 1]$ the mass of banks that choose decentralization. The mass of banks investing in the high-return project is then $(1 - d)\frac{1}{2} + d = \frac{1+d}{2}$. In an interior equilibrium, this pins

[2]Decentralization without the cost is never (strictly) optimal as it yields the same return as centralization. If in addition decentralization is subject to a (small) disadvantage, for instance because of agency problems, it will be dominated by centralization.

[3]We have assumed that the identity of the high-return project is independently distributed from the identifiable characteristic. One may argue that when financing is more difficult (because there are less banks that are available to process it, or because it is urgent), returns are likely to be higher. This would only serve to strengthen the benefit of decentralization.

down the share of decentralized banks d^* through the condition

$$\frac{1}{2}r(\frac{1+d^*}{2}) = c, \tag{2}$$

that is, the profits from decentralization and centralization are equalized. Existence of the interior equilibrium is guaranteed by $\frac{1}{2}r(\frac{1}{2}) < c < \frac{1}{2}r(1)$. Note that the equilibrium condition only pins down the mass of banks that operate in a decentralized manner; individual banks are indifferent as to their organizational form.

We can derive several predictions.

1. *Decentralized banks lend at higher interest rates*: When a decentralized bank lends the (average) net interest rate is is r, compared to $\frac{r}{2}$ for a centralized bank.

2. *Decentralized banks are more likely to lend when a borrower has high (temporary) demand.*

3. *Decentralized banks lend to a wider set of borrowers and respond faster to common information*: Decentralized banks choose the project that offers the highest return in each period. As the identity of that project will differ from period to period (in other words, borrower demand fluctuates), this requires them to not specialize in whom they fund. They can also respond faster to emerging lending opportunities because they do not require approval by central.

3 Decentralization measure

3.1 Conceptual explanation

Organizational forms are difficult to quantify because they have many different dimensions. In our context we are interested in the extent to which lending decisions in a banking group are taken at the local (subsidiary-level) as opposed to the parent-level. Most large banks have a centralized software for loan approvals. However, loan approval systems still differ widely in how much power they leave to local loan officers. For example, is there an automated loan decision following data input by the local officer, or are loan decisions still discretionary? At which level are the data inputs, in particular credit ratings, set? Is the are (dollar) threshold below which a subsidiary make own decisions, and how high is it? How often does the parent overrule loan proposals made by subsidiary?

On top of this, there is potential divergence of formal and real authority. A large part of the literature has focused on *de jure* measures of decentralization. For example, formal authority of procurement officers (Best, Khan, and Prat (2021)), local managers in SOE (Kala, 2024) and of local branches to set deposit rates (Dlugosz, Gam, Gopalan, and Skrastins (2024)). However, such authority may differ from actual decision-making (Aghion and Tirole, 1997). For example, a superior may have formal power but in practice just rubber-stamp decisions, or be too busy to interfere. Or, a subordinate may make decisions to please his superior even when he has formal power.[4]

We will measure decentralization reflected in actual decision-making. The idea is simple. In a centralized organization, different subsidiaries should evaluate a borrower of a given type similarly as they apply firm-wide lending principles, resulting in similar decisions. In a decentralized setting, subsidiaries make their own decisions, leading to outcomes that can be different (the next section discusses in detail the sources of such differences). We can thus quantify decentralization by the extent to which different subsidiaries of a group reach different decisions when presented with a comparable lending opportunity.

Our measure has two distinct features. First, it is a comprehensive measure of decentralization and will capture the various dimensions of decentralization according to their influence on the relevant decision variable. Second, as it is derived from actual decisions, it incorporates the notion of real authority.

[4]Some papers quantify decentralization using surveys (for example, Beqiraj, Cao, De Haas and Minetti (2025)), which is somewhat inbetween formal and real authority. See in particular the questions in Section 4.

3.2 Construction of the measure

We will derive our measure from lending decisions in the *syndicated loan market*. The syndicated loan market is a world wide market for loans to predominantly large corporates, and a high number of the global banks and their subsidiaries participate in it. We have granular data on individual loan decisions in this market, allowing to control for a wide set of factors.

Consider that a subsidiary s uses the following loan pricing model

$$r_{s,f,t} = a_{s,t} + A_s X_{f,t} + D_{f,t} + \varepsilon_{s,f,t}, \tag{3}$$

where $r_{s,f,t}$ is the interest rate charged on a specific loan to firm f in year t, X is a vector of loan and borrower characteristics (such as loan size, presencce of collateral or leverage), and $D_{f,t}$ is firm demand (through the lens of the framework in Section 2, it indicates the presence of the high-state). Our construction of the decentralization measure starts from how a subsidiary deviates from the *global* pricing of firms. For this we condition on borrower-year fixed effects, which absorb the demand term $D_{f,t}$ but also borrower-specific characteristics The pricing deviation is given by

$$res_{s,f,t} := r_{s,f,t} - r_{f,t} = (a_{s,t} - a_t) + (A_s - A)X_{l(f),t} + \varepsilon_{s,f,t}, \tag{4}$$

where $X_{l(f),t}$ denotes loan-specific characteristics.

The decentralization measure of a *Group* is defined as the expected difference in pricing residuals on two loans made by different subsidiaries of the group. In the case of two subsidiaries s_1 and s_2 this difference is given by (see Appendix A for the general definitions):

$$DI_{Group}(t) = E[|res_{s_1,t} - res_{s_2,t}|]. \tag{5}$$

In a fully centralized group, we would expect similar pricing deviations on loans, resulting in zero (or low) $DI_{Group}(t)$. However, in a decentralized setting, loan decisions will be made by independent loan officers in each subsidiary, resulting in higher $DI_{Group}(t)$.

See Figure 1 for an example.

We can also define a decentralization measure specific to a *subsidiary s*. Subsuming all other subsidiaries of the group into a hypothetical single subsidiary $-s$, this measure can be expressed as:

$$DI_{Sub\ s}(t) = E[|res_{s,t} - res_{-s,t}|]. \tag{6}$$

Subsidiary-level decentralization may differ from group decentralization when there are more then two subsidiaries. As an example, a group may allow a specific subsidiary to be decentralized because of limited agency conflicts in this subsidiary, even when the entire group lends itself more to a centralized structure.

Equation (4) shows that there are three sources of pricing differences: loan pricing by the subsidiary may differ from other loans issued by the group due to a different constant pricing difference of loans in each period ($a_{s,t}$), due to different pricing of observable factors A_s, and due to idiosyncratic pricing of specific borrowers $\varepsilon_{s,f,t}$.

Let us start with pricing differences due to observable factors (A_s). This is the cleanest measure as it cannot be confounded by soft information (which could result in differences in the firm-specific terms $\varepsilon_{f,t}$) nor by different hurdle rates for a subsidiary (for example, a subsidiary may face capital shortages in a given year, and hence require a higher a_t). Such a difference may arise when for example a subsidiary has different attitudes towards specific industries or borrower types (such as large and small firms).

Next, pricing differences arise due to subsidiaries pricing loans generally different in a given year ($a_{s,t}$). This may be due to different views on the credit cycle, or animal spirits.

Finally, we consider dispersion arising from the attitude towards specific borrowers ($\varepsilon_{s,f,t}$). One interpretation is really the one of an error term. Each individual will look at each loan decisions differently, and hence arrive at different results. For example, Gao, Karolyi and Pacelli (2018) show that distracted loan officers price loans differently. Another one, are personal tastes vis-a-vis the firm. Karolyi (2018) finds that loan officers charge different rates in the syndicated loan market to borrowers with whom they have a personal relationship (distinct from the relationship between bank and firm). In addition, Ravina (2024) finds that loan officers may charge different rates depending on borrower gender, beauty and race, and that this depends on borrower characteristics (for example, a male may charge different rates to a female than a female).

To calculate DI, we first run a global regression on all loans in the sample, yielding estimates of $\widehat{a}_t$, $\widehat{A}$ and $\widehat{D}_{f,t}$. From this we can calculate the global pricing of a specific loan ($r_{f,t} = \widehat{a}_{s,t} + \widehat{A}X_{f,t} + D_{f,t}$), and hence the pricing deviation by a subsidiary on this loan ($res_{s,f,t}$).

We approximate $E[|res_{s1,t} - res_{s2,t}|]$ by the average distance in pricing deviations of all relevant loans pairs (see Appendix A for the full definitions). In the case of the group-level DI, these are all pair of loans that can be formed across all pairs of subsidiaries, in the case of the subsidiary-level DI these are all pair of loans that can be formed across the subsidiary itself and the set of all other subsidiaries.

In robustness, we also consider a normalized DI measure. The motivation is that deviations from global pricing (in absolute terms) may be larger for loans that have higher spreads, resulting in a higher $DI-$measure. To account for this, we use pricing deviations scaled by the global pricing for that loan ($\frac{res_{s,x,t}}{r_{x,t}}$) in the construction of DI.

Note: The DI is based on the average distance of *loan pairs*. An alternative measure could be derived from first averaging pricing residuals $res_{s,x,t}$ within a subsidiary, and then calculating the distance across subsidiaries. However, this would already average out parts of the price residuals (the one coming from the firm-specific terms $\varepsilon_{s,f,t}$, and partially also from A_s). This problem is compounded by the fact that the number of loans varies widely across subsidiaries (some subsidiaries issue more than 100 loans in a year, others only a few). As a result, subsidiaries (and groups) that issue more loans would (mechanically) appear less decentralized based on that measure.

3.3 DI and lending rates: A numerical example

In the following we consider a simple example that illustrates how a decentralized bank has both higher DI (Section 3.2) and lends at higher rates (Section 2).

In the framework of Section 2, DI is zero regardless of organizational form. However, suppose that managers make (random) adjustments to the pricing of loans each year.

Specifically, consider that the low-state project gets on average charged 200 bps in the market, and a high-state project 220 bps. Each year, loan officers make a pricing adjustment of either 10 bps and -10 bps (with equal likelihood). In the case of a centralized bank, the pricing error is fully correlated across subsidiaries (for example, because the yearly lending rate adjustment is prescribed by the central approval system) whereas for a decentralized bank it is independently distributed across subsidiaries. DI for a centralized bank is then 0, whereas for a decentralized bank it is 10 bps. At the same time, the average interest rate charged by a centralized bank is 210 bps (since it funds a high-state project with probability $\frac{1}{2}$), whereas for a decentralized bank it is 220 bps (since it only funds high-state projects). Thus, there is a positive relationship between DI and average rates.

3.4 Calculating DI from syndicated loan data

We will use data on syndicated loans from the DealScan database provided by Loan Pricing Corporation (LPC). Our sample comprises 324,496 syndicated loans issued between 2000 and 2019. Syndicates consist of lead arrangers (who set the pricing) and passive participants. For the construction of the measure we will use only the lead arrangers, treating loans with more than one lead arranger as separate observations.

The loans are issued by 1118 subsidiaries affiliated with 327 bank groups. Our analysis will take place at the facility level (a syndication typically consists of several facilities), which will informally refer to as a loan. Each subsidiary issues an average of 30 loans (facilities) per year, ranging from 1 to 1725.

To calculate pricing deviations, we run first the following loan pricing model:

$$Spread_{l,f,t} = \beta_1 * Loan\ Terms_l + \beta_2 * Loan\ Size_l + \beta_3 * Loan\ Type_l + \beta_4 * Loan\ Purpose_l + \lambda_{f,t} + \epsilon_{l,f,t} \quad (7)$$

The dependent variable $Spread_{l,f,t}$ represents the spread (interest rate r minus the risk free rate) in the loan facility l to firm f in year t. The independent variables, *Loan Terms*, encompass other loan terms such as *Covenant*, *Collateral*, and *Maturity*, as well as *Loan Size*, *Loan Type*, and *Loan Purpose*. As discussed in Section 3.2 we include borrower x year fixed effects ($\lambda_{f,t}$), which controls for demand but also borrower risk.

For a specific loan and lender (lead arranger) s, the estimated global model allows us to calculate the deviation from the global pricing $res_{s,l,f,t}$ ($= Spread_{s,l,f,t} - \widehat{Spread}_{l,f,t}$). From equations (8) and (9) in the appendix we can then calculate the decentralization indices for groups and subsidiaries, reported in Table 1. For comparison, the table also reports a dispersion measure across loans of a subsidiary with subsidiaries belonging to *other* groups. We can see that dispersion across groups is higher, indicating that loan pricing within groups is (at least) partially centralized.

4 *DI* and survey data

The purpose of this section is to provide external validation for *DI*. We will do this by examining how it correlates with survey data on bank centralization. We use the first wave of the BEPS surveys, which are carried out by the EBRD and are nationally representative surveys of banks in mostly European transition countries.[5] A few of the banks are also subsidiaries of global banking groups that are active in the syndicated loan market. The survey contains several questions relating to the organization of decision-making in the group, such as "How important is the influence of your parent bank in shaping the credit risk assessment of clients?" and "Does your parent bank set annual targets for your bank in terms of credit growth?" A link to the survey including the questions can be found here (the most relevant questions are in Q47 and Q50).

Table 2 displays the results of regressions of *DI* on BEPS survey responses. The variable *Average relevant* represents a bank's averaged responses to questions that are relevant to lending decentralization. A higher value in the BEPS data indicates that the bank is *more* centralized.

Given the limited number of subsidiaries that are both present in the survey and in

[5]This survey has been used in other studies to measure decentralization, see Beqiraj, Cao, De Haas and Minetti (2025)).

the syndicated loan market, we start reporting regressions with subsidiary DI at the loan-pair level (that is, the dependent variable is $|res_{s,x,t} - res_{-s,y,t}|$ instead of averaging as in equation (9)) and cluster standard errors at the subsidiary level. This allows to exploit that the precision of DI_{Sub} varies across subsidiaries (because subsidiaries differ widely in the amount of loans they issue) and that the influence of a lead arranger varies across deals (because there can be several lead arrangers). We can see in column (1) that the coefficient of *Average relevant* is negative and significant.

In column (2) we control separately for a centralization index of functions that are less relevant to lending (*Average irrelevant*). Similar to *Average relevant*, it is created from averaging responses to questions that cover other aspects of centralization, for example, in the area of operational risk management. If our measure picks up primarily decentralization in lending, we would expect it to be less correlated with other dimensions of decentralization. In column (2) we see that the coefficient on *Average relevant* is insignificant, whereas the coefficient on *Average relevant* remains significant.

Column (3) takes into account that the power of an individual lender to set prices may vary across loans as there can be several lead arrangers. Specifically, we weigh observations by the inverse of the number of lead arrangers. The coefficient on the variable of interest increases in absolute terms, and remains significant.

In column (4), we run regressions at the subsidiary-level. The coefficient of *Average relevant* remains negative and significant. The number of observations in this regression is limited (there are 135 subsidiaries for which the DI can be calculated and that are present in the BEPS survey, however, only 12 provided responses to decentralization-relevant questions). Figure 2 provides the scatter plot of DI and *Average relevant*. The figure shows a strong negative relationship between DI and the BEPS-decentralization that is not driven by outliers.

These results provide evidence that DI is negatively related to survey responses on centralization of lending. At the same time, it is not related to survey responses on centralization of other decisions, suggesting that it contains lending-specific information.

Table 3 reports correlations on the individual survey responses underlying *Average* *relevant* (these questions can be found here). A large number of individual question responses are strongly negatively related to our measure.

5 Nimbleness

We now examine the predictions of Section 2. We will investigate the behaviour of decentralized banks, in terms of whether they are present in a syndicate when lending rates are high, under what other credit conditions they join a syndicate, and how specialized they are in their lending profile. In contrast to the analysis of pricing decisions (Section 3), we now also examine the banks that are not lead arrangers in the syndicate, that is, are not setting the pricing of the loan. Table 4 contains the summary statistics for the sample.[6]

5.1 Nimble banks and interest rates

Table 5 investigates first whether when a given participant in the syndicate is more decentralized, interest rates are higher (Prediction 1).[7] For each subsidiary participating in a syndicate, we relate the spread (interest rate) of the loan originated in the syndication to the subsidiary's decentralization measure. In the regression we control for "project" characteristics using a set of loan and borrower controls. Importantly though, we do not include borrower (x year) fixed effects as this controls for the presence of a "high-state" project (we return to these fixed effects in Table 8). We use the five-year (lagged) average of DI as a measure of decentralization.

Column (1) presents first the regression for DI_{Group}; in column (2) we then switch to using subsidiary-level DI, which will also be our baseline. In either case, the coefficient on DI obtains a positive and significant coefficient, with similar magnitudes. In economic terms, a one standard deviation change in DI in the baseline results is a change in

[6]The (loan-level) values for DI differ markedly from the (subsidiary- and group-level) values in Table 1. An explanation for this is that subsidiaries and groups differ widely in the amount of loans they make, leading to a higher weighting of more active banks in Table 4.

[7]Running regressions at the participant level has the advantage that we can control for subsidiary and group characteristics. Our empirical specification for analysing loan pricing in syndication follows closely prior literature, e.g., Santos (2010).

the loans spread of 19 bps, about 12% of the mean. Thus, when a decentralized bank participates in a syndicate, rates are meaningfully higher. Since the regressions control for borrower and loan factors, such as leverage and loan collateralization, this suggests also higher risk-adjusted interest rates.

Figure 3 shows the coefficients of the baseline regression including a dummy for each DI-decile. We can observe a monotonic relationship between interest rates and DI almost over the entire range.

Column (3) presents a specification controlling for bank characteristics. We include both subsidiary-level controls (such as size and capitalization) as well as group x year fixed effects, thus fully controlling for group-level effects. The sample falls by 41% (mostly on account of imperfect matching of syndicate participants to balance sheet data). The coefficient on DI remains of similar size and significant. This result is noteworthy since it shows that Prediction 1 also works within groups (that is, subsidiaries that are more decentralized within a group earn a higher rates).

In column (4) we control for two other dimensions of pricing differences. A subsidiary may price loans generally differently, not only specifically vis-a-vis its group. If this is the case, our DI may possibly also pick up general discretion in loan pricing (for a discussion of the latter, see Cerqueiro, Degryse and Ongena, 2011), and not exclusively decentralization. To investigate, we construct a measure of price dispersion vis-a-vis subsidiaries of other groups ($DI_{other\ groups}$). Specifically, for each loan-pair that is used for the calculation of the DI, we replace the loan not belonging to the focal subsidiary with a random loan originated by another group. We also construct a separate measure capturing within-subsidiary variation in pricing ($DI_{within\ sub}$). A subsidiary may be flexible in its pricing across loans, which may, or may not, be a consequence of decentralization. We construct this measure similar to the DI, but now using all pair of loans extended by the subsidiary itself. The results in column (4) show that after controlling for these other dimensions of dispersion, DI still obtains a positive and significant coefficient. Interestingly, the within-sub DI also enters with a positive and significant coefficient.

In column (5) we restrict the sample to passive participants in the syndicate. In a typical syndication, the lead banks first negotiate the loan terms (including the interest rate) with the borrower. They then take this proposal to the market, allowing other banks to join (though the loan terms may still be revised after this phase if there is not enough demand). The sample falls now by 54%. However, the coefficient on DI remains positive and significant.

Whereas column (5) splits the pricing decision and joining decision by separating into active and passive participants, column (6) does so by splitting observations across time. Specifically, we calculate the DI measure using only observations before 2010, and run the baseline regression only from 2010 onward. The DI measure is again positive and significant. This result also suggests that decentralization at banks is fairly sticky, as past decentralization predicts outcomes many years into the future.

In column (7) we replace the five-year (lagged) average of the DI with the one-year lag. This measure is likely more noisy, which is reflected in a lower coefficient on the DID, though still very significant.

In column (8) we restrict the sample to cross-border loans, defined as borrower and syndicate participant not being from the same country. Prior literature (e.g., Berger, Black, Rosen (2005), Liberti and Mian (2009), Karolyi and Jacewitz (2018)) has shown that proximity can afford informational advantages and result in reliance on soft information. The coefficient remains positive and significant, consistent with our mechanism being orthogonal to information.

The pricing difference between two loans is expected to be greater (in absolute terms) when loans have higher spreads. Column (9) corrects for this using the normalized measure described in Section 3.2. The coefficient on DI remains positive and significant, and with an implied economic magnitude comparable to the baseline model (18 bps instead of 19 bps).

5.2 Mergers

In Table 6 we examine exogenous variation in decentralization using bank mergers. Prior literature has shown that targets converge towards the characteristics of acquirers following the merger. We apply this idea to decentralization.

We start with all bank mergers incorporated in the Dealscan-Compustat link provided in Schwert (2018). We create shocks to decentralization using the DI of the acquirer in the five years prior to the merger.[8] Our dataset contains 9184 loan observations involving targets in mergers, arising due to a total of ten mergers.

Table 6 contains the results. In this table we include group fixed effects to control for time-invariant group characteristics, including its level of decentralization. DI_{merger} is a variable that is zero for a target prior to a merger, but takes the value of the acquirer DI (calculated over the five years prior to the merger) following the merger. We also include a merger dummy to capture the average effect of a merger. In column (1) the coefficient on DI_{merger} takes a positive value and is significant. The size of the coefficient is similar to the baseline estimate of column (2) in Table 5. In column (2) we restrict the baseline to only target observations, obtaining a coefficient similar to the one for the entire sample.

5.3 Sources of price dispersion

Table 7 examines next different sources of loan rate dispersion. There are three such such sources as discussed in Section 3.2: pricing differences due to A, a_t and $\varepsilon_{f,t}$. Columns (1) to (3) reproduce the baseline specification from Table 5, isolating each source separately. Column (4) further refines the dispersion arising from A, excluding differences that may possibly arise when subsidiaries specialize in firms with different characteristics X (see Appendix A). In all four cases, the coefficient is positive and significant.

An interesting question is the relative importance of the different dimensions. A comparison of economic significance (based on standard deviation changes) shows that they are all important. The largest effect arises for the pricing of observable factors and the error term (15 and 18 bps); the lowest effect is for the yearly effect and the observable factors keeping constant loan characteristics (10 bps and 12 bps).

[8] We only have one M&A where we have also the target DI and where the target keeps lending after the M&A. We thus create shocks using acquirer values only. For similar data reasons we also cannot study actual convergence in DI of target and acquirer post merger.

There are two important takeaways from this exercise. First, lending decisions create dispersion among different dimensions, and they are all related to interest rates. Second, our results are not driven by soft information or (different) hurdle rates as the results hold when we only include differences in the pricing of observeables (columns (1) and (4)).

5.4 Demand and urgency

We next investigate borrower demand. Our framework predicts that decentralized banks are more likely to lend (join a syndicate) when borrowers have high demand (Prediction 2). The first part of Table 8 examines this prediction using different proxies for high demand. In column (1) we directly identify borrower demand in a given year. For this we regress total borrowing of a firm in a year on borrower-year and lender-year fixed effects (the latter control for supply effects).[9] The borrower-year fixed effects from this regression give us borrower demand. We then regress the DI of each participant in the syndicate on the demand measure, controlling for borrower fixed effects (thus isolating variation in borrower-demand over time). In column (1) borrower demand obtains a positive and significant coefficient. This provides the first piece of evidence that decentralized banks are more likely to lend when demand is high.

In column (2) we exploit a sudden materialization of demand, in the form leveraged buy outs (LBOs). An LBO typically leads to large, unanticipated, increase in funding requirements. LBO offerings also have to be put together quickly, that is, there is urgency. As such, these are ideal opportunities for decentralized banks. In column (2) we can see a positive and significant coefficient on LBOs, that is, when there is a LBO, decentralized banks are more likely to lend. Importantly, LBOs (and to a large extent, borrower demand generally) are observeable characteristics, suggesting that the results are not due to soft information.

Murfin and Petersen (2016) investigate seasonal periods of high demand. They show that firms that borrow in certain periods during the year (specifically, January, February

[9]The matching of lenders to borrowers may be endogenous. We thus run an alternative exercise excluding lender-year fixed effects, and obtain similar results.

and August) have more urgent demand and also pay higher interest rates. They show that this price differential can be sustained in an equilibrium where banks specialize in different periods and borrowers have heterogeneous demands. It is a priori not clear whether decentralized banks are part of the group that specialize on high demand months. The reason is that these months are in principle known ex-ante and thus do not require flexibility on the side of banks. In column (3) we include the high-demand periods of Murfin and Peterson, and find no significant association. As said, this may reflect that the benefit of decentralized banks is that they can act more flexibly, but in this case the (seasonal) incidence of high-demand is known.

The remaining columns of the table consider another way to examine the effect of demand: the inclusion of borrower fixed effects in the loan pricing regression. If the pricing advantage of decentralized banks is due to borrower demand, then the advantage should weaken if we include such fixed effects. We include subsequently finer fixed effects (borrower FE, pseudo-demand effects akin to Degryse et al. (2019) and borrower-year fixed effects). We can see that in each case, the coefficient shrinks in size, confirming the demand-side interpretation of our results. The results also rule out explanations based on decentralized banks being able to set higher rates on the same borrower than other banks, for example due to higher bargaining power. Interestingly, the results remain (statistically) significant even when we control for borrower-year fixed effects (the economic significance though is very small: a one standard deviation change in the DI is associated with a higher rate of less than 1 bp). A potential reason for this is within-year variation in borrower demand, as considered earlier in the table (e.g., due to LBOs or seasonal variation in urgency).

5.5 Flexibility

Last, Tables 9 and 10 examine whether decentralized banks lend more flexibly (Prediction 3). First, a bank that wants to exploit lending opportunities arising from high demand has to be flexible in the industries and countries it lends to (as opportunities will materialize in different parts of the market each year). Columns (1)-(3) in Table 9 investigate this prediction using bank-level concentration of lending. The latter is proxied by the HHI of a bank's lending portfolio in a given year based on i) industries, ii) countries, iii) industry-country pairs. The regression results indicate that decentralized banks have less concentrated portfolios (indicated by a low HHI) on all the three dimensions. This is consistent with decentralized banks being more flexible in their lending, allowing them to better capture opportunities. The lower specialization of decentralized banks also speaks against an informational interpretation of our main result in Table 5 as less specialization leads to less information, and not an informational advantage (see, e.g., Acharya, Hasan, Saunders (2006)).

Table 10 considers the "speed" dimension of flexibility. Our framework suggests that decentralized banks can react faster to lending opportunities (for instance because central approval is not required). This affords them with another advantage when a commonly observed lending opportunity realizes. In Table 10 we examine lending responses to a country's credit cycle. For each (borrower) country we create a dummy for the four quarters prior to the peak of the credit cycle, and a dummy for the four quarters past the peak, plus the peak itself (the omitted category are periods in which there is no expansion of the credit cycle). We then regress a lender's DI on the credit cycle dummies. The regression shows that decentralized banks react more when there is an expansion, and significantly more in the beginning of the expansion. This result is consistent with decentralized banks reacting faster to changes in (aggregate) conditions.[10]

6 Conclusions

This paper has examined how organizational flexibility influences investment decisions. We developed a novel measure of decentralization based on observed differences in the pricing of loans across subsidiaries within banking groups. We found that decentralized banks earn economically meaningful higher spreads on loans to borrowers with comparable characteristics. There was evidence that this can be explained by decentralized banks

[10]Interestingly, it suggests that decentralization may also have implications for financial stability as prior literature has shown that risky loans are particularly made during the later part of the cycle, e.g., Dell'Ariccia, Igan and Laeven (2012) and Keys, Mukherjee, Seru and Vig (2010).

better exploiting lending opportunities arising from high demand and higher urgency. They do so by being more flexible in terms of the industries and countries they lend to, and by reacting more quickly changes in aggregate lending conditions. Overall, the results suggest that a decentralized organization provides material benefits by enabling more flexible decision-making.

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Figure 1: A centralized and a decentralized group

Figure 2: Correlation between *DI* and BEPS survey responses

This figure plots subsidiary-level DI against the average score of relevant questions in the BEPS survey (*Average relevant*).

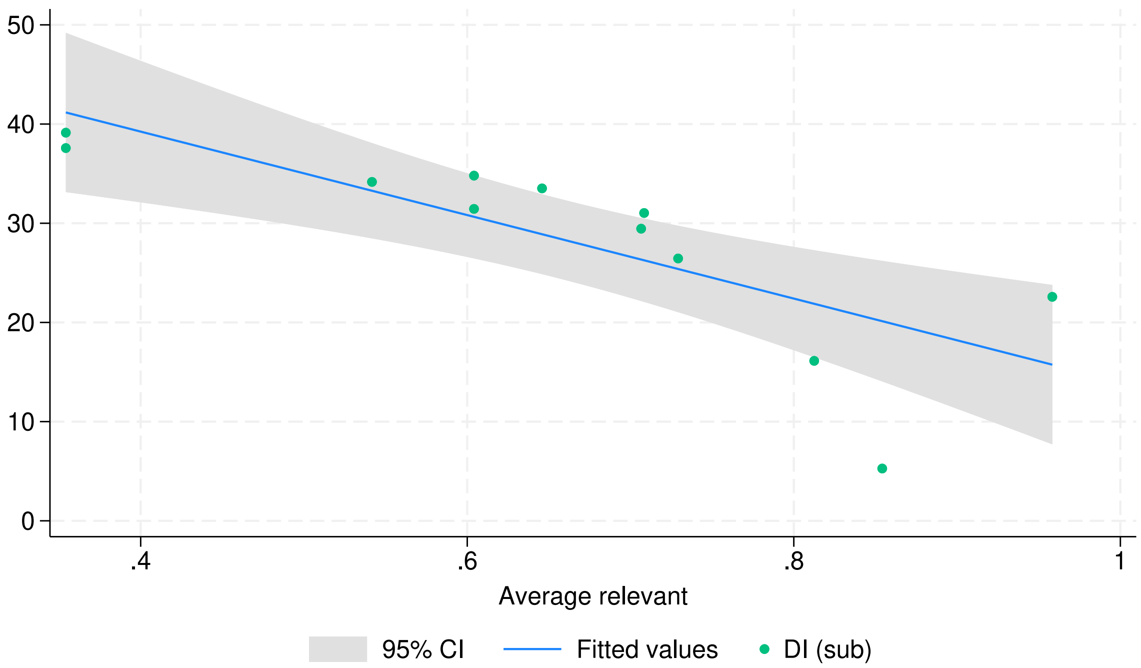

Figure 3: Loan spreads and *DI* deciles

This figure plots the coefficient estimates of dummy variables indicating deciles of DI in a regression of loan spreads with the same control variables as in regression 2 of Table 5. The coefficients are standardized so that the fifth decile is at zero.

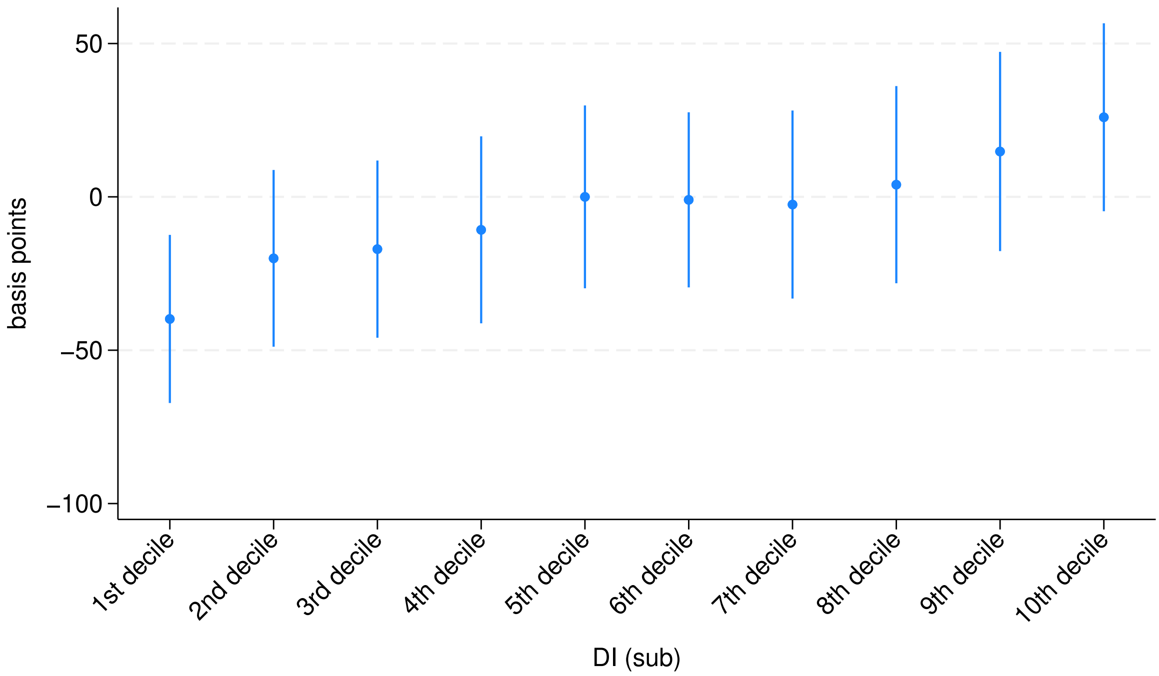

Table 1: Group and subsidiary level *DI*

This table presents decentralization measures for groups and subsidiaries.

	Observations	Mean	Median	SD	Min	Max
DI (group-year)	1,470	27.60	22.33	22.41	0	222.6
DI (group-year, other groups)	1,470	35.25	32.17	17.26	0.714	149.9
DI (sub-year)	4,908	27.70	22.35	22.80	0	478.0
DI (sub-year, other groups)	4,908	34.29	29.87	22.55	0	481.1

Table 2: Correlations with BEPS survey responses

This table shows regressions of *DI* on BEPS responses at loan-pair level and subsidiary level. *t-statistics* in parentheses are calculated using standard errors clustered by subsidiary. * Significant at 10% level. ** Significant at 5% level. *** Significant at 1% level.

	OLS		GLS	OLS
	(1)	(2)	(3)	(4)
	DI (loan-pair)	DI (loan-pair)	DI (loan-pair)	DI (sub)
Average relevant	-23.079***	-26.293***	-39.310***	-42.083***
	(-12.49)	(-20.37)	(-13.47)	(-4.07)
Average irrelevant		4.611		
		(1.73)		
Observations	15953	15953	15953	12
Adjusted R^2	0.009	0.009	0.020	0.586

Table 3: Correlations with individual BEPS survey questions

This table shows correlations between *DI* and individual BEPS responses at the loan-pair level. *t-statistics* in parentheses are calculated using standard errors clustered by subsidiary. * Significant at 10% level. ** Significant at 5% level. *** Significant at 1% level.

vq47d	-6.659***	(-4.28)
vq47h	-6.674***	(-3.28)
vq47l	-5.942	(-1.49)
vq50a	-30.399**	(-2.60)
vq50b	-12.838***	(-5.16)
vq50c	4.004	(0.61)
vq50d	1.580	(0.23)
vq50e	-15.068***	(-4.17)
vq50f	-10.465**	(-2.40)
vq51e	-10.743	(-1.28)
vq51f	-14.861***	(-4.16)
vq51h	-18.920***	(-18.66)
Observations	15953	

Table 4: Summary statistics for the baseline interest rate and decentralization regressions

The table present summary statistics for the loan-level analysis on decentralization and interest rate

	Observations	Mean	Median	SD	Min	Max
Spread	76,328	161.0	135	122.7	17.50	750
DI (group)	76,328	33.42	31.26	13.76	10.14	81.70
DI (sub)	76,328	33.82	31.42	14.47	10.08	83.56
DI (other groups)	76,328	38.60	34.91	12.87	16.41	76.67
DI (within sub)	74,349	37.00	33.17	16.98	6.944	100.8
DI-N (sub)	76,328	0.152	0.143	0.0676	0.0427	0.381
DI (sub, lagged 1-year average)	71,790	33.63	29.53	17.80	6.576	99.95
DI (slopes)	74,205	130.9	130.8	32.35	55.96	210.9
DI (sub-year)	74,205	3.338	2.620	2.928	0.0380	16.64
DI (residual)	74,205	30.91	29.20	15.43	4.524	80.27
DI (slopes, const covariates)	74,205	18.01	15.57	12.14	0.424	66.60
Loan size	76,328	19.65	19.74	1.459	14.91	22.35
Covenants	76,328	0.433	0	0.568	0	1.609
Collateral	76,328	0.373	0	0.484	0	1
Borrower size	76,328	13.78	13.75	2.131	8.578	19.00
Borrower ROA	76,328	0.884	0.0344	3.453	-1.161	25.88
Borrower leverage	76,328	0.290	0.262	0.223	0	1.137
Has credit	76,328	0.173	0	0.378	0	1
Maturity	76,328	52.05	60	24.42	7	216
Revolver	76,328	0.476	0	0.499	0	1
Loan Purpose	76,328	0.357	0	0.479	0	1
Demand	75,543	0.523	0.524	1.070	-4.375	4.203
LBO	76,328	0.0501	0	0.218	0	1
High demand month	76,328	0.185	0	0.388	0	1
Concentration (sector)	76,328	0.0708	0.0377	0.105	0.000000439	1
Concentration (country)	76,328	0.372	0.299	0.328	0	1
Concentration (country-sector)	76,328	0.0411	0.0130	0.0953	0	1

Table 5: Decentralization and interest rates

This table presents the relationship between loan spreads and decentralization. t-statistics, shown in parentheses, are calculated using standard errors clustered at the combined subsidiary-year level, except for regressions 1, in which standard errors are clustered at the group-year level. * Significant at 10% level. ** Significant at 5% level. *** Significant at 1% level.

	Baseline sample				Participants only	Baseline sample		Cross-border loans	Baseline sample
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Spread	Spread	Spread	Spread	Spread	Spread	Spread	Spread	Spread
DI (group)	1.401***								
	(13.94)								
DI (sub)		1.310***	1.196***	0.865***	0.970***			0.765***	
		(14.19)	(4.43)	(7.46)	(9.98)			(11.02)	
DI (other groups)				0.018					
				(0.13)					
DI (within sub)				0.546***					
				(5.55)					
Pre-2010 average DI (sub)						1.562***			
						(13.41)			
DI (sub lagged 1-year average)							0.720***		
							(10.53)		
DI-N (sub)									290.643***
									(13.95)

Bank size			6.308**						
			(2.24)						
Bank Equity/assets			82.343**						
			(2.31)						
Bank sd(ROA)			-236.168***						
			(-2.93)						
Loan size	-15.765***	-15.733***	-20.534***	-15.826***	-13.891***	-15.502***	-15.202***	-20.462***	-15.759***
	(-23.92)	(-23.79)	(-27.72)	(-23.81)	(-15.19)	(-13.97)	(-21.15)	(-32.91)	(-23.99)
Covenants	-7.475***	-7.776***	-6.434***	-7.256***	-2.828	-45.345***	-6.929***	1.381	-8.711***
	(-4.23)	(-4.61)	(-3.19)	(-4.30)	(-1.46)	(-19.31)	(-3.92)	(0.78)	(-5.12)
Collateral	93.967***	94.047***	90.304***	93.396***	92.408***	80.226***	97.102***	97.213***	93.530***
	(52.77)	(52.56)	(38.65)	(51.14)	(39.40)	(30.40)	(53.29)	(50.63)	(52.23)
Borrower size	-2.679***	-2.678***	-2.611***	-2.707***	-3.949***	-1.462***	-2.776***	-2.988***	-2.698***
	(-9.47)	(-9.66)	(-7.76)	(-9.69)	(-10.65)	(-2.90)	(-9.79)	(-8.66)	(-9.76)
Borrower ROA	-0.041	-0.041	0.036	-0.004	0.207	1.090***	-0.031	-0.498***	-0.052
	(-0.28)	(-0.28)	(0.19)	(-0.03)	(1.42)	(4.39)	(-0.21)	(-2.89)	(-0.36)
Borrower leverage	17.052***	17.096***	18.377***	16.799***	24.578***	29.332***	17.149***	23.368***	17.217***
	(7.00)	(7.17)	(6.36)	(6.96)	(7.72)	(6.85)	(7.03)	(7.92)	(7.25)
Has credit	26.342***	26.351***	21.708***	26.579***	27.851***	34.346***	26.333***	21.346***	25.913***
	(15.55)	(15.62)	(11.06)	(15.59)	(12.54)	(12.79)	(15.17)	(11.67)	(15.51)
Maturity	0.482***	0.480***	0.469***	0.473***	0.606***	0.443***	0.484***	0.477***	0.489***
	(14.91)	(15.09)	(11.62)	(14.68)	(15.13)	(6.70)	(14.36)	(12.19)	(15.40)

Revolver	-27.055***	-26.997***	-29.227***	-27.128***	-18.958***	-39.621***	-26.348***	-27.632***	-27.441***
	(-22.19)	(-22.94)	(-17.57)	(-22.51)	(-14.50)	(-21.98)	(-21.16)	(-23.15)	(-23.41)
Loan Purpose	3.859***	4.041***	-7.441***	3.748**	5.789***	-5.277**	6.009***	-4.778***	3.306**
	(2.64)	(2.78)	(-4.50)	(2.54)	(3.33)	(-2.20)	(3.78)	(-3.04)	(2.29)
Observations	76328	76328	44357	74349	34796	26744	71790	45414	76328
Adjusted R^2	0.370	0.369	0.434	0.372	0.397	0.307	0.365	0.419	0.371
Year FE	Yes	Yes	-	Yes	Yes	Yes	Yes	Yes	Yes
Group * Year FE	No	No	Yes	No	No	No	No	No	No

Table 6: Decentralization and interest rates following mergers

This table presents the impact of the acquiror group's decentralization on the spreads of loans originated by target banks following a merger. t-statistics, shown in parentheses, are calculated using standard errors clustered at the group-year level. * Significant at 10% level. ** Significant at 5% level. *** Significant at 1% level.

	Baseline sample	Target banks only
	(1)	(2)
	Spread	Spread
DI (acquiror group pre-merger)	1.567**	1.478**
	(2.08)	(2.11)
Post merger	-11.262	0.847
	(-0.36)	(0.03)
Loan size	-20.022***	-24.728***
	(-49.98)	(-13.92)
Covenants	-1.690	0.426
	(-1.42)	(0.15)
Collateral	85.198***	100.858***
	(57.94)	(23.26)
Borrower size	-0.245	-2.762***
	(-1.11)	(-4.47)
Borrower ROA	-0.535***	0.176
	(-4.89)	(0.39)
Borrower leverage	18.954***	15.481**
	(10.51)	(2.56)
Has credit	30.214***	5.863
	(22.74)	(1.62)
Maturity	0.298***	0.272***
	(11.41)	(3.35)
Revolver	-25.027***	-19.026***
	(-26.67)	(-6.28)
Loan Purpose	14.166***	0.840
	(13.50)	(0.23)
Observations	141494	9184
Adjusted R^2	0.336	0.426
Group FE	Yes	Yes

Table 7: Decomposition

This table examines the link between different components of decentralization and loan spreads. t-statistics, shown in parentheses, are calculated using standard errors clustered at the combined subsidiary-year level. * Significant at 10% level. ** Significant at 5% level. *** Significant at 1% level.

	(1) Spread	(2) Spread	(3) Spread	(4) Spread
DI (slopes)	0.486***			
	(13.38)			
DI (sub-year)		3.278***		
		(7.68)		
DI (residual)			1.246***	
			(14.58)	
DI (constant covariates)				1.004***
				(11.57)
Loan size	-16.037***	-15.350***	-16.838***	-15.441***
	(-23.82)	(-21.02)	(-25.89)	(-21.17)
Covenants	-9.693***	-7.346***	-6.420***	-7.777***
	(-5.44)	(-4.16)	(-3.88)	(-4.42)
Collateral	95.298***	98.238***	93.640***	97.139***
	(52.77)	(55.57)	(51.56)	(54.80)
Borrower size	-2.670***	-2.645***	-2.733***	-2.664***
	(-9.45)	(-9.32)	(-9.76)	(-9.46)
Borrower ROA	-0.069	-0.105	-0.031	-0.064
	(-0.47)	(-0.71)	(-0.21)	(-0.43)
Borrower leverage	16.987***	16.208***	16.838***	16.461***
	(7.04)	(6.64)	(7.04)	(6.79)
Has credit	25.880***	27.135***	25.107***	27.141***
	(15.47)	(15.52)	(15.00)	(15.59)
Maturity	0.509***	0.483***	0.480***	0.481***
	(15.60)	(14.56)	(15.04)	(14.62)
Revolver	-28.788***	-26.859***	-28.173***	-27.449***
	(-23.52)	(-21.85)	(-23.86)	(-22.33)
Loan Purpose	3.338**	5.981***	2.054	5.615***
	(2.21)	(3.73)	(1.42)	(3.54)

Observations	74205	74205	74205	74205
Adjusted R^2	0.374	0.365	0.381	0.369
Year FE	Yes	Yes	Yes	Yes

Table 8: Demand and urgency

This table investigates whether decentralized banks are more likely to lend when a borrower has high demand and whether demand weakens the link between decentralization and interest rates. t-statistics, shown in parentheses, are calculated using standard errors clustered at the borrower-year level in regressions 1 and 2, and at the combined subsidiary-year level in regressions 3 to 12. * Significant at 10% level. ** Significant at 5% level. *** Significant at 1% level.

	(1)	(2)	(3)	(4)	(5)	(6)
	DI (sub)	DI (sub)	DI (sub)	Spread	Spread	Spread
Demand	0.380***					
	(4.87)					
LBO		2.912***				
		(5.47)				
High demand month			0.066			
			(0.43)			
DI (sub)				0.246***	0.182***	0.039***
				(7.14)	(5.82)	(3.85)
DI-N (sub)						
Loan size	-0.046	1.328***	1.329***	-20.967***	-9.770***	-4.831***
	(-0.93)	(12.76)	(12.73)	(-31.88)	(-20.60)	(-10.57)
Covenants	0.348***	0.046	-0.135	-10.573***	-8.966***	-4.249
	(2.91)	(0.14)	(-0.41)	(-4.63)	(-6.66)	(-0.98)
Collateral	1.335***	3.672***	4.016***	82.429***	31.803***	-35.366***
	(9.28)	(13.25)	(14.08)	(31.12)	(16.21)	(-7.97)
Borrower size	-0.071***	-0.018	-0.019	-5.113**	3.598***	
	(-2.70)	(-0.60)	(-0.65)	(-2.40)	(3.02)	
Borrower ROA	0.019	-0.009	-0.008	0.406*	0.221	
	(1.22)	(-0.56)	(-0.48)	(1.93)	(0.93)	
Borrower leverage	0.179	-0.417	-0.436	14.033***	9.257**	
	(0.71)	(-1.53)	(-1.60)	(4.04)	(2.33)	
Has credit	0.155	1.899***	1.873***	7.620***	-6.829**	
	(0.96)	(6.56)	(6.49)	(3.91)	(-2.29)	
Maturity	-	0.008**	0.010***	0.697***	0.430***	0.600***
	(-0.11)	(2.52)	(3.23)	(19.49)	(12.92)	(16.09)
Revolver	-0.029	0.860***	0.839***	-28.574***	-26.140***	-22.112***

	(-0.42)	(5.30)	(5.17)	(-21.69)	(-27.47)	(-27.99)
Loan Purpose	1.016***	3.619***	3.495***	-12.077***	-12.564***	-15.950***
	(9.78)	(11.73)	(11.40)	(-5.89)	(-10.85)	(-6.15)
Observations	105356	106649	106649	76068	76015	75359
Adjusted R^2	0.394	0.176	0.174	0.739	0.748	0.899
Year FE	Yes	Yes	Yes	-	Yes	-
BCIYS FE	No	No	No	Yes	No	-
Borrower FE	Yes	No	No	No	Yes	-
Borrower-year FE	No	No	No	No	No	Yes

Table 9: Lending focus

This examines the link between decentralization and concentration in lending portfolios. t-statistics, shown in parentheses, are calculated using standard errors clustered at the combined subsidiary and year levels. * Significant at 10% level. ** Significant at 5% level. *** Significant at 1% level.

	(1)	(2)	(3)
	Concentration (sector)	Concentration (country)	Concentration (country-sector)
DI (sub)	-0.001***	-0.002***	-0.001***
	(-5.03)	(-4.61)	(-4.83)
Observations	58905	35087	135254
Adjusted R^2	0.010	0.013	0.009
Year FE	Yes	Yes	Yes

Table 10: Reaction to cycle

The table examines how decentralized banks lend over the credit cycle of the borrower. t-statistics, shown in parentheses, are calculated using standard errors clustered at the borrower * year-quarter levels. * Significant at 10% level. ** Significant at 5% level. *** Significant at 1% level.

	(1)
	DI (sub)
Pre-peak credit cycle quarters [t-4,t-1]	1.102***
	(5.96)
Post-peak credit cycle quarters [t,t+4]	0.696***
	(3.92)
Loan size	-0.022
	(-0.44)
Covenants	-0.644***
	(-3.45)
Collateral	0.830***
	(3.54)
Borrower size	0.083
	(0.56)
Borrower ROA	-0.017
	(-0.47)
Borrower leverage	-0.472
	(-0.90)
Has credit	0.844*
	(1.71)
Maturity	0.001
	(0.60)
Revolver	-0.352***
	(-5.14)
Loan Purpose	0.470***
	(3.62)
Observations	79520
Adjusted R^2	0.306
p value of H0: Post <= Pre	0.042
Year-quarter FE	Yes
Borrower FE	Yes

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Appendix

A Calculation of the decentralization measures

Consider a group with k ($k \geq 2$) subsidiaries. For each subsidiary s we can order the loans issued by that subsidiary in year t as $1, 2, ..., n_s(t)$.

We can first calculate the $DI(Group)$ by the average distance in all pricing deviations of all possible loan pairs that can be formed across subsidiaries of the group. The measure is calculated as

$$\widetilde{DI}_{Group}(t) = \frac{\sum_{u=1}^{k-1} \sum_{v=u+1}^{k} \sum_{x=1}^{n_u(t)} \sum_{y=1}^{n_v(t)} |res_{u,x,t} - res_{v,y,t}|}{\sum_{u=1}^{k-1} \sum_{v=u+1}^{k} n_u(t)\, n_v(t)} \tag{8}$$

The decentralization index for a specific subsidiary s can be calculated from all possibly pairs of loans between that subsidiary and all other subsidiaries of the group

$$\widetilde{DI}_{Sub\ s}(t) = \frac{\sum_{u=1,u\neq s}^{k} \sum_{x=1}^{n_s(t)} \sum_{y=1}^{n_u(t)} |res_{s,x,t} - res_{u,y,t}|}{\sum_{u=1,u\neq s}^{k} n_s(t)\, n_u(t)} \tag{9}$$

To calculate the normalized difference measure DI_N, we replace $res_{\cdot,x,t}$ in (9) with we pricing errors scaled by level of global pricing for that loan: $(\frac{res_{\cdot,x,t}}{r_{x,t}})$.

To calculate the five-year average difference measure, we consider in **??** and **??** not only loan pairs that can be formed within year t, but also across all years $t-4,\ t-3,\ t-2,\ t-1,\ t$.

We also construct decentralization measures for the three decompositions, based on A_s ($DI(slope)$), $a_{s,t}$ ($DI(sub-year)$) and $\varepsilon_{s,f,t}$ ($DI(residual)$). For this we replace $|res_{s,x,t} - res_{u,y,t}|$ in (9) with respectively $|(A_s - A)X_{x,t} - (A_u - A)X_{y,t}|$, $|(a_{s,t} - a_{u,t}|$ and $|\epsilon_{x,t} - \epsilon_{y,t}|$.

Note that the measure based on observables ($DI(slope)$) may also affected when both subsidiaries make different loans.This may confound our decomposition measure when subsidiaries tend to make loans to companies of different characteristics (different X_t) *and* the group deviates differently from global pricing for these characteristics (for example, one subsidiary focuses on small firms and the other on large firms, and the group underprices small firms but overprices large firms). We hence construct an alternative decomposition measure $DI(slope, constantcovariates)$ using $|(A_s - A_u)X_{x,t}|$.

In Table 5 we control for different dimensions pricing differences. The first measure, $DI(acrossgroups)$, measures differences between a subsidiary and subsidiaries of other groups. For this we replace each loan y of subsidiary u ($u \neq s$) in (9) with a loan randomly drawn from all loans issued by subsidiaries of other groups in year t. The second measure, $DI(withinsub)$, instead considers all pairs of loans issued by the subsidiary itself:

$$\widetilde{DI}_{Within\ Sub\ s}(t) = \frac{\sum_{x=1}^{n_s(t)} \sum_{y=1,y\neq x}^{n_s(t)} |res_{s,x,t} - res_{s,y,t}|}{(n_s(t) - 1)\frac{n_s(t)}{2}} \tag{10}$$

Table A1: Data description and sources

Variable	Description	Data Source
Spread	The all-in spread drawn in basis points.	DealScan
DI (group)	Pairwise absolute differences in loan spread residuals, averaged within each bank group over the past five years and lagged by one year. Loan spread residuals are calculated using a global loan pricing model. Pairwise differences are computed across all combinations of loans between distinct subsidiaries within the same bank group (excluding the parent bank).	Dealscan
DI (sub)	Pairwise absolute differences in loan spread residuals, averaged within each subsidiary over the past five years and lagged by one year. Loan spread residuals are calculated using a global loan pricing model. Pairwise differences are computed across all combinations of loans between the subsidiary and all other subsidiaries of the same bank group (excluding the parent bank).	Dealscan
DI (other groups)	Pairwise absolute differences in loan spread residuals, averaged within each subsidiary over the past five years and lagged by one year. Loan spread residuals are calculated using a global loan pricing model. Pairwise differences are computed across a set of loans randomly sampled with replacement from subsidiaries of other bank groups.	Dealscan
DI (within sub)	Pairwise absolute differences in loan spread residuals, averaged within each subsidiary over the past five years and lagged by one year. Loan spread residuals are calculated using a global loan pricing model. Pairwise differences are computed across all combinations of loans made by the subsidiary.	Dealscan
DI-N (sub)	Pairwise absolute differences in loan spread residuals normalized by the predicted spread, averaged within each subsidiary over the past five years and lagged by one year. Loan spread residuals are calculated using a global loan pricing model. Pairwise differences are computed across all combinations of loans between the subsidiary and all other subsidiaries of the same bank group (excluding the parent bank).	Dealscan
DI (sub, lagged 1-year average)	Pairwise absolute differences in loan spread residuals, averaged within each subsidiary over the past year. Loan spread residuals are calculated using a global loan pricing model. Pairwise differences are computed across all combinations of loans between distinct subsidiaries within the same bank group (excluding the parent bank).	Dealscan
DI (slopes)	Pairwise absolute differences in loan spread residuals, averaged within each subsidiary over the past five years and lagged by one year. The loan spread residual for each loan is calculated as the predicted loan spread using the global pricing model, minus the predicted loan spread based on observable loan and borrower characteristics and borrower-year effects using subsidiary-specific pricing models that also include subsidiary-year and borrower-year fixed effects. Pairwise differences are computed across all combinations of loans between the subsidiary and all other subsidiaries of the same bank group (excluding the parent bank).	Dealscan

Table A1: Data description and sources (continued)

Variable	Description	Data Source
DI (sub-year)	Pairwise absolute differences in loan spread residuals, averaged within each subsidiary over the past five years and lagged by one year. The loan spread residual for each loan is calculated as the subsidiary-year fixed effect from subsidiary-specific pricing models that include observable loan and borrower characteristics, subsidiary-year fixed effects and borrower-year fixed effects. Pairwise differences are computed across all combinations of loans between the subsidiary and all other subsidiaries of the same bank group (excluding the parent bank).	Dealscan
DI (residual)	Pairwise absolute differences in loan spread residuals, averaged within each subsidiary over the past five years and lagged by one year. The loan spread residual for each loan is calculated as the residual from subsidiary-specific pricing models that include observable loan and borrower characteristics, subsidiary-year fixed effects and borrower-year fixed effects. Pairwise differences are computed across all combinations of loans between the subsidiary and all other subsidiaries of the same bank group (excluding the parent bank).	Dealscan
DI (constant covariates)	Pairwise absolute differences in predicted loan spreads, averaged within each subsidiary over the past five years and lagged by one year. For each loan-pair, the predicted loan spread difference is the difference in the predicted loan spreads, using subsidiary-specific pricing models that include observable loan and borrower characteristics, subsidiary-year fixed effects and borrower-year fixed effects, calculated at one of the loan's observable characteristics (i.e. keeping covariates constant). Pairwise differences are computed across all combinations of loans between the subsidiary and all other subsidiaries of the same bank group (excluding the parent bank).	Dealscan
Borrower size	The natural logarithm of the total assets of the borrower at the end of the year prior to the loan.	WorldScope
Borrower ROA	The borrower's net income over total assets ratio for the year prior to the loan.	WorldScope
Borrower leverage	The borrower's total liabilities over total assets ratio at the end of the year prior to the loan.	WorldScope
Loan size	Natural log of the facility amount in USD.	Dealscan
Covenant	Dummy variable indicating that the loan has a net worth or financial covenant.	Dealscan
Collateral	Dummy variable which equals one if DealScan reports the loan as secured and zero otherwise.	Dealscan
Maturity	The maturity of the loan is months.	DealScan
Revolver	Dummy variable which equals one if the reported loan type is either "Revolver/Line < 1 Yr.", "Revolver/Line >= 1 Yr.", "364-Day Facility", "Revolver/Term Loan", or "Limited Line".	Dealscan
Loan Purpose	Dummy variable indicating that the loan is primarily for corporate purposes.	Dealscan
Demand	The borrower-year fixed effect from a regression of loan amount in USD and borrower-year fixed effects and subsidiary-year fixed effects.	Dealscan

Table A1: Data description and sources (continued)

Variable	Description	Data Source
LBO	Dummy variable indicating that the primary loan purpose is "LBO".	Dealscan
High demand month	Dummy variable indicating that the loan was originated in January, February, or August.	Dealscan
Concentration (sector)	The HHI of a subsidiary's total syndicated lending in a given 2-digit SIC sector relative to its total syndicated lending in a given year.	Dealscan
Concentration (country)	The HHI of a subsidiary's total syndicated lending in a given country relative to its total syndicated lending in a given year.	Dealscan
Concentration (country-sector)	The HHI of a subsidiary's total syndicated lending in a given 2-digit SIC sector in a given country relative to its total syndicated lending in a given year.	Dealscan
Pre-peak credit cycle quarters [t-4,t-1]	Dummy variable indicating the four quarters before the peak of the borrower country's unfiltered financial cycle. Peaks are identified following the methodology of Claessens et al. (2011).	Adarov (2018)
Post-peak credit cycle quarters [t,t+4]	Dummy variable indicating the five quarters following the peak—including the peak quarter—of the borrower country's unfiltered financial cycle. Peaks are identified following the methodology of Claessens et al. (2011).	Adarov (2018)