The effect of allocating decision rights on the generation, application, and sharing of soft information

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Abstract

Should a bank take small to medium sized companies at face value? Research in both accounting and finance has tried to answer this question by studying the use of so-called soft information, which is qualitative, hard to verify, and costly to transfer. We study how the generation, sharing, and application of this kind of information is affected by the location of knowledge and the allocation of decision rights. Specifically, we examine how operational decisions are affected if controls are introduced that limit the decision rights of loan officers. To that end, we exploit a quasi-natural experiment at a large European bank to study whether reallocating decision rights away from loan officers enables or impedes incorporating soft information into operational decision-making. The reallocation of decision rights was prompted by the regulator who required the bank to restructure their loan decision process. Our findings indicate that this reduction in decision rights enables better integration of soft information in credit application decisions. These findings are robust to controlling for strategic loan-sorting behavior, manager fixed effects, and the likelihood of acceptance. We also document that this improved integration of soft information is driven by a change in behavior by the loan officers and that it results in better loan outcomes.

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1. Introduction

Economic theory suggests that firms are better off granting decision rights to employees with the best knowledge of a given situation as long as the firm also implements controls to prevent these employees from behaving opportunistically (Jensen and Meckling, 1992; Milgrom and Roberts, 1992; Raith, 2008). This expectation is supported by empirical work (Abernethy, Bouwens, and van Lent, 2004; Moers, 2006). What happens, however, to the quality of decision-making if the firm limits the decision-making rights of these employees? We study this question by examining whether implementing additional controls enables or impedes the incorporation of soft information in the operational decision-making of a large bank.

Theory offers contradictory predictions on the effect of reallocating decision rights away from the agent responsible for collecting and processing soft information. Based on the work of Aghion and Tirole (1997), one might argue that centralization will make the role of the agent less prominent, which will lead the agent to shirk information collection efforts. This prediction is supported by the argument that introducing additional agents into the process increases the communication costs of soft information (Dessein, 2002; Dewatripont and Tirole, 2005). Work by Holmström and Milgrom (1991), however, suggests a reduction in task multidimensionality can increase agents effectiveness in collecting and processing information. Constant, Kiesler, and Sproull (1994) support this prediction by arguing that career opportunities motivate agents to exert more effort when their actions become directly visible to a higher hierarchical party.

Previous studies (e.g. Campbell, 2012, Qian, 2015, Liberti 2017) have looked into the context where the individual banks unilaterally decide to extend the decision rights of loan officers on granting loans and establishing loan rates. In these papers it is suggested that the extension of decision rights led loan officers to collect more (soft) information which in turn enhanced their decisions. We examine a reduction of the decision rights of the loan officer implemented by the bank to follow up a call that the regulator made on the bank. The call entailed that the bank increased the level of scrutiny in evaluating whether a loan should be granted or not. We argue that in this context loan officers are more willing to accept a limitation in their decision rights as central management can claim that the central bank pointed to shortcomings in the loan application process. In addition, the context may lead loan officers to step up their effort to collect information on whether a loan is warranted and what are the appropriate conditions to grant the loan. We argue that loan officers are sensitive to the procedure that is followed to arrive at a decision that impacts directly on their decision rights. Employees who consider a procedure to be fair, are more likely to subscribe to the outcome of that procedure (e.g., Fehr and Gchter, 2000). We believe that studying the potential effect of the regulator is important as well-functioning legal and regulatory system in creating an effective market economy is now widely accepted (Besely, 2015). Hart (2009) claims that it is not clear why the parties cannot design their own penalties to control bad behaviour. In case of loan decisions, it would be unclear why bank management by itself could not arrive at the decision to cut the decision right of their loan officers. We argue that the costs of doing so may be too high in the absence of a regulator. The mandate of the regulator allows th bank management to justify its decision with reference to the regulator. This would enhance the likelihood of employees accepting the decision of the firm to curb decision rights.

We exploit an externally imposed organizational design change in credit applications for small to medium-sized companies at a large European bank to study these contradictory predictions. Specifically, the bank limited the ability of loan officers to approve loans, based upon soft information they had collected. It reallocated their decision rights to risk approvers and required the loan officers to share their information with the approvers. This setting is especially suitable to study the use of soft information because it is characterized by the low availability of verifiable information. Soft information, such as subjective assessments on the quality of management, is collected solely by the loan officer and assists in the assessment of the credit worthiness of potential borrowers (Agarwal and Hauswald, 2010; Uchida, Udell, and Yamori, 2012; Drexler and Schoar, 2014).

Our empirical design exploits the shock to the banks loan-application reviews that came with the introduction of this new procedure. This shock, which is exogenous from the perspective of the loan officers, creates a quasi-natural experiment. Jensen and Meckling (1992) provide a framework to describe the expected effect of a shock of this sort in an organizations design. In our case, the loan officers soft information is specific knowledge that is costly to transfer. The initial design of the banks credit reviews minimized transfer costs by allocating decision rights to loan officers. This design, however, exacerbated the agency problem because higher-level managers could not verify the information underlying loan decisions (Jensen and Meckling, 1992). External pressures to impose additional controls on credit approvals let the upper-level management redesign the credit process, requiring loan officers to obtain approval from the risk department.

We use a loan application-level dataset for the years 2013 and 2014 compiled from a variety of proprietary internal information systems of the bank. These information systems primarily contain hard information related to the loan applications. Soft information is qualitative and unverifiable, impeding its storage in a similar fashion. A common approach to operationalize soft information is to create a proxy based on an internal risk rating corrected for an estimated amount of integrated hard information (Berg, Puri, and Rocholl, 2014; Qian, Strahan, and Yang, 2015). We avoid these indirect proxies, like Campbell, Erkens, and Loumioti (2014) and Campbell, Erkens, and Loumioti (2016), by creating a variable based on the subjective interest-rate adjustment that the bank makes for some loans. The main determinant of the interest rate charged on loans is hard information. The optional adjustment is designed to incorporate the availability of additional soft information. Adjustments therefore proxy for the degree to which available soft information impacts operational decision-making.

Our results support soft information being better used in loan applications following the reallocation of decision rights. This result is driven by a change in behavior of the loan officers, and is robust to controlling for loan officer fixed effects and the inclusion of rejected loan applications. Our analysis shows that this change in behavior is associated with improved outcomes as measured by the risk rating trends in the 15 months following loan granting.

This paper extends knowledge in accounting and finance on the gathering, sharing, and application of soft information. Our setting enables us to adopt a strong identification strategy without losing track of the underlying business process. With the credit reviews for corporate loan applications as a control group, we can account for bank specific, geographical, and economic time trends by using a differences-in-differences design. We also can correct for strategic loan-sorting behavior by the loan officer using a Heckman selection model, and we directly proxy for soft information using the discretionary part of the interest rate.

Our paper makes several contributions. We first extend the findings of Qian et al. (2015) by studying an explicit shock to an organizations design, applying a direct measure of soft information, and using a differences-in-differences design to rule out confounding events and time trends. We likewise broaden the findings of Liberti and Mian (2009) by showing that hierarchical distance does not impede the sharing and incorporation of soft information. And we add to the stream of literature led by Campbell et al. (2016) on the portability of soft information. Campbell et al. (2016) document that soft information can be transferred over time and between employees at the same hierarchical level. We show that soft information can also be transferred between hierarchical levels, even after a reallocation of decision rights. We also complement a growing literature on the effect of risk management in monitoring loan officers (e.g., Berg, 2015).To the best of our knowledge this is the first study that directly examines the effects of a regulator imposing the introduction of a mandatory risk management system into an established setting.

From a management control point of view analytical (Frey, 1993), experimental (Falk and

Kosfeld, 2006) and archival work (Campbell, Epstein and Martinez Jerez, 2011) suggests that agents perform worse if their actions are controlled by central management because they resent the firm decision. We study how an external justification may lead agents to take accept centralization so that they would abstain from actions that impact outcomes negatively.

Our results also provide insight into the difficulties banks encounter in evaluating loans for small and medium-sized enterprises. These kinds of borrowers have a large economic importance and mainly rely on bank financing (Uchida et al., 2012). In the recent years, especially following the credit crisis of 2008-2009, banks have been criticized for being insufficiently willing to lend to small and medium-sized applicants (Wehinger, 2014). Our study delves into a banks screening procedures to investigate factors that influence the likelihood of loan acceptance. The majority of others papers are constrained by data limitations and cannot include these types of analyses.[1]

2. Hypotheses Development

A trade-off between agency costs and transfer costs

The classical agency problem is characterized by information asymmetry between the principal and the agent. In the framework of Jensen and Meckling (1992), this information asymmetry is defined by two types of information: general and specific. These types differ mainly in their transfer costs when people want to share information. Specific information is costlier to transfer. In a theoretical situation with selfless agents, the optimal solution would be to transfer general information upward and transfer decision rights downward to those agents in possession of the specific information. The possibility of opportunism, however, complicates this solution; organizational design must account for agents who might use their decision

[1]With some notable exceptions such as Agarwal and Hauswald (2010)

rights opportunistically. In a situation with substantial specific information, this results in a trade-off between transfer costs (information lost by transfer) and agency costs (suboptimal use of the information).

The concept of soft information

Soft information can be hard to define (Liberti and Mian, 2009). We investigate a setting that relates closely to the one described by Berger, Klapper, and Udell (2001) and Petersen (2004). These authors agree on three characteristics of soft information: it is difficult to generate, hard to verify, and costly to share. Hard or quantitative information, in contrast, is easy to store and can be objectively transmitted (Petersen, 2004). Examples of hard information used in credit evaluation are internal risk ratings as well as information about an applicants industrial segment and the geographical location. Examples of soft information are the loan officers assessment of the quality of management, the sustainability of involvement by key persons, the feasibility of the underlying credit purpose, the sustainability of the business model, and the risk profile of important suppliers.

Based on the theoretical framework presented below, we expect that the reallocation of decision rights affects how soft information influences decision-making. Our first hypothesis reflects this expectation.

Hypothesis 1. *Moving decision rights to higher hierarchical levels affects the effectiveness of considering soft information in decision-making.*

2.1. Reallocating decision rights enables effective use of soft information.

Reduced task multidimensionality

The efficient advocacy hypothesis (Berg, 2015) as developed by Holmström and Milgrom, 1990, 1991), posits that a superior outcome can be achieved by splitting the responsibility for a task into several separate objectives. In our research setting, the risk approver is put in place to act as a safeguard and decrease the likelihood that risk is either misjudged or not appropriately acted upon by loan officers. From the perspective of the loan officer, knowing someone else is in charge of reviewing credit decisions shifts attention away from risk assessment. Put differently, such a reduction in task multidimensionality allows the loan officer to dedicate more time and effort on the aspect of gathering and sharing information, increasing the availability of soft information to be incorporated into the credit decision.

Knowledge sharing as a cost benefit trade-off

Career considerations influence the behavior of loan officers (e.g. Cole, Kanz, and Klapper, 2015). Loan officers who perform well can expect to receive promotions either through increased authority or better positions in different departments. Constant et al. (1994) approach knowledge-sharing as a cost-benefit trade-off. In our setting, that implies that the introduction of the risk approver increases the exposure of the loan officer. Knowledge sharing thus becomes a way for loan officers to improve their career prospects. This is an example of the generation and sharing of high quality soft information being influenced by extrinsic motivators. As discussed by Lin (2007), however, there also may be are intrinsic motivators that influence the sharing of information. Adding additional agents increases the reciprocal benefits, knowledge self-efficacy and enjoyment of helping others by sharing high quality information.

Increase task clarity through the introduction of a supervisor

Gibbons and Henderson (2012) suggest that introducing an additional supervisor improves task clarity for loan officers. From the perspective of relational contract theory, there are two important components of knowledge: task understanding and relational knowledge. Understanding procedural guidelines and executing them falls under the category of task understanding, but the abstract nature of soft information makes it hard for the bank to create such guidelines (Campbell et al., 2016). Relational knowledge is defined as an understanding of what each party can and is expected to do. Employees of the risk department have greater authority and are thus expected to better understand these undocumented rules and expectations. By mandating the loan officer to interact with these risk employees, the bank might aim to improve the understanding among loan officers about what soft information they are expected to gather and share.

A reduction of soft information that is being strategically withheld

Loan officers can strategically communicate soft information to affect the outcome of the credit application by withholding parts of their private information (Crawford and Sobel, 1982). Hertzberg, Liberti, and Paravisini (2010), for example, find that loan officer rotations improve the accuracy of communications because of a reduction in strategic motivation to withhold information. The incentive of loan officers to strategically withhold information is also influenced by the hierarchical distance within the authorization chain (Dessein, 2002). Mosk (2014) documents that limiting the authority of loan officers to approve applications increases their incentives to share information. In our setting, the introduction of a risk approver might therefore increase the benefits of strategically sharing information. This, in turn, may increase the amount of available soft information.

The actions of the regulator

Regulators create social value in the extent they set rules that allow parties to conclude contracts that could not surface if it was not for that rule (Hart, 2009). This situation may exist, for instance, when individual agents are able to exploit their information advantage at the cost of the other party. In the case of loan decisions it is not immediately clear under what conditions bank management and loan officers are unable to conclude (adapt) their contract. As theory suggests, agents may be put off if management decides that the bank makes better decision if they centralize decision making on loans. However, if it is the case that the bank is better off with centralization provided that loan officers subscribe to centralization regulators may provide the bank with the necessary justification to centralize decision making. This condition exists if a central manager is better able than a loan officer to process information guiding the decision to grant the loan and/or set the conditions. In that case the loan officer specializes in collecting soft and hard information, while the central manager interprets the data ta make the loan decision. The benefit would be further enhanced if the loan is prepared to extend her/his information collection effort. This would enhance the amount of information available to the decision maker. Even when talents of central managers and loan officers are the same, decision making will improve provided that the loan officer starts to collect additional information in response to centralization of decision making.

Combining these theoretical considerations results in our first sub-hypothesis.

Hypothesis 2a. *Moving decision rights to higher hierarchical levels increases the effectiveness of considering soft information in decision-making.*

2.2. Reallocating decision rights impedes effective use of soft information.

A less prominent role for the loan officer

While the efficient advocacy hypothesis highlights the benefits of splitting responsibilities, there is another stream of literature that emphasizes potential downsides. By introducing an additional agent into the authorization chain, the role of the loan officer is made less prominent (Aghion and Tirole, 1997). Recent papers, such as one by Qian et al. (2015) and Liberti, 2017, have shown that an increase in responsibility increases the effort put into the generation of soft information. Reversing that logic results in the expectation that reducing the loan officers responsibility leads to less effort exerted to generate and share soft information. In summary, the amount of responsibility given to the loan officer is a delicate matter. Too much responsibility might cause the loan officer to act opportunistically whereas too little could result in a loss of information being generated and shared.

The negative effects of evaluative pressure

Introducing a risk approver increases the exposure of the information generated by the loan officer. Increased exposure might cause the loan officer to hesitate about being creative in generating soft information. This change in behavior is explained by the finding of Campbell, Epstein, and Martinez-Jerez (2011) that increasing the intensity of monitoring can discourage out-of-the-box thinking and experimentation. The loan officer might experience an increased amount of evaluative pressure, which, combined with uncertainty about the expectations of upper-level management, could cause them to reduce their efforts to generate information.

Increased communication costs

The introduction of a risk approver also increases communication costs. The loan officer must consider that there is an additional agent, from a different department, who will have to receive, understand, and interpret the loan officers information. As a result, the loan officer will have to devote additional effort to preparing soft information in a way that maximizes the likelihood that it will be correctly received and interpreted. Only then can the risk approver act upon information in the way the loan officer intended. To compensate for the increased costs, the loan officer may reduce the effort put into generating and sharing soft information. The risk approver may, in turn, not act upon this soft information because the costs of correctly understanding and interpreting it are too high (Bolton and Dewatripont, 1994; Dessein, 2002; Dewatripont and Tirole, 2005).

Actions of the regulator

In case that the bank justifies centralization of loan decision without convincing the loan officer that this decision is motivated by the regulator, implementation may impair the data collection effort of the loan officer. In that case the loan officer may decide to leave decision making and data collection to central management. They will only collect information in the extent this is mandated by central management.

Combining these theoretical considerations results in our competing sub-hypothesis.

Hypothesis 2b. *Moving decision rights to higher hierarchical levels decreases the effectiveness of considering soft information in decision-making.*

3. Research Setting

The research setting for this study is a large European bank that offers banking, insurance, and asset management services. Data for one geographical segment, from August 2013 through August 2014, was compiled from the internal information systems of the bank. This geographical segment is an environment with a large and economically significant network of small to medium-sized enterprises. Throughout this period, the bank was consistently ranked in the top 25 of largest European banks.

3.1. Credit assessments

Loan rates

The bank generates a suggested loan rate for each application. This rate is comprised of a risk-based component (based on hard information) and a cost-based component that includes charges for services such as document preparation, underwriting, and origination. In the case of applications from small and medium-sized businesses, the suggested loan rate is relatively high, compared to those offered to bigger companies. The reason is that the underlying risk-based component and the cost-based adjustment are both higher on average. These higher rates stem from to the relative lack of hard information on applicants and the difficulty for the bank of covering the largely fixed application expenses with the small principle amounts of these loans. The loan officers, however, can propose a rate adjustment based on any material soft information that they have collected.

The suggested loan rate for these applications is, on average, substantially higher than the interest rate that would be calculated based on the actual probability of default by small and medium-sized businesses. As a result, loan officers typically propose loan rate reductions when they incorporate soft information into the interest rate of the applications. [2,3]

Application process

In the small and medium-sized sector, the bank receives many applications that generally request relatively small amounts of credit. Evaluation is thus standardized to efficiently cope with the volume. Only a limited amount of hard information is readily available about the applicants, which increases the importance of soft information, when its available (Uchida et al., 2012). The banks guidelines, however, emphasize only the importance of soft information without providing comprehensive guidance on how to gather and store it (Campbell et al., 2016).

A loan application starts with an applicant requesting a loan via regular channels, such as the website or a call to the bank. Another option is for the applicant to directly contact his or her relationship manager at the bank. Depending on the channel through which an application arrives, it is screened based on a set of guidelines that require the applicant to have the appropriate set of documents, such as a Chamber of Commerce registration. If the basic conditions are met, the application is taken into consideration via a front office manager, who will handle the early communications. In many circumstances, the application is discontinued at this early stage, often at the initiative of the applicant. Applications that pass this early stage are classified as potential credit candidates and are assigned a loan officer to handle and initiate communications with the purpose of gathering the desired information.

[2] This is also reflected by the fact that these adjustments are referred to as loan rate discounts within the bank. An adjustment therefore interacts with the final interest rate in the following way: a positive (negative) adjustment reduces (increases) the interest rate.

[3] A counterintuitive implication of this typical overstatement is that net negative soft information frequently leads to an interest-reducing adjustment if the calculated interest rate is still overstated after incorporating the negative soft information. These scenarios will obviously reduce the interest rate less, compared to a situation of net positive soft information, but they can still be interest reducing.

Based on the soft information gathered by the loan officer and the hard information provided by the applicant, a loan proposal is suggested by the loan officer. It includes hard information, such as internal ratings and details on the prior credit history of the applicant. It also includes soft information, such as communications and meeting summaries combined with any subjective assessments of the loan officer. The application is then sent to a front-office member. The file contains both the proposal of the loan officer and a write-up of the soft and hard information used to develop the proposal. The loan officer and front-office manager may then discuss the proposal, and they make a joint decision to sign off on the loan file.

3.2. Policy change

At the beginning of 2014, a policy change was implemented. Some of the decision rights of loan officers to grant loans were moved to the risk department. In other words, loan officers were no longer allowed to prepare the full credit application and make an offer to the client without the explicit approval of the risk department. This change was primarily triggered by a policy change initiated by a regulator, which required the bank to implement tougher controls in its credit reviews. The rationale behind the banks choice to alter the decision rights was that upper-level management viewed the original review process as lacking in the ability to generate appropriate risk profiles for applicants.[4] Soft information is an important part of an accurate risk profile, especially for small and medium-sized businesses (Uchida et al., 2012; Drexler and Schoar, 2014). The loan officers are the account managers of the loan applicants and are thus the only employees tasked with collecting soft information. The bank decided to involve the risk department toward the end of the application process. The risk department then has the final say on the loan proposal and the acceptance of an application. The risk department can ask loan officers to elaborate on their initial loan proposals. If the risk department disagrees with the loan officer, its decision prevails.

[4]The bank did not decide to alter the decision rights because they perceived the interest rate to be consistently too high or too low. The combination of external pressure with a perceived inability of the loan officers to generate an appropriate risk profile were the primary drivers of the organizational design change.

3.3. Role of the loan officer

Incentives of the loan officer

The majority of activities by loan officers involve managing their accounts. These activities range from providing services to customers to negotiating with the clients to increase the likelihood that loan payments arrive on time (e.g. forbearance negotiations). The incentive system for the loan officers does not include performance-related bonuses. Loan officers receive a fixed wage determined by tenure, and the banks culture motivates through the possibility of promotion.

Loan officers are, therefore, not explicitly given individual targets in terms of the number of loans they are expected to sell. Occasionally, they are encouraged to increase their sales activity if the total number of granted loans in a period was falling short of the projected amount. These inducements, however, do not play a leading role in promotion decisions. Instead, the likelihood of promotion, and the performance appraisal in general, is primarily based on how well loan officers manage their clients. Standard advancement paths include a promotion to servicing corporate loans or a promotion to a different department such as the risk department. Promotions are characterized by not only an increase in responsibilities but also an increased mandate for the total amount of outstanding credit that the officer can manage.

Discretion of the loan officer

For our study, it is of particular interest how the soft information collected by the loan officer is incorporated into the loan proposal and the final outcome of the credit application. In the settings of similar papers, soft information is usually integrated into the internal risk rating (Berg, 2015; Qian et al., 2015) of a client. In the application process we study, however, these internal credit ratings are solely based on hard information and are kept clear from any discretionary influence by the loan officer. Based on policy documents and conversations with bank employees, we have identified two key stages at which the collected soft information can influence applications.

In the early stage of an application, front office employees have some discretion over the applications that they pre-screen. The majority of early rejects or cancellations are due to inability of the applicant to comply with basic requirements, such as the uploading of hard information. At this early stage, however, the front office employee is the sole possessor of any soft information gathered from communications with the applicant. Many of these applications do not reach the point of being logged in the main application information system.

After the application has passed these early stages, it is entered into the final application processing system. At this stage, the loan officer determines the specifics of the loan proposal. The loan officer has discretion over two main choices: the credit construction and the interest rate. The credit construction determines the type of product (e.g., working capital loan, overdraft loan, regular fixed interest loan) that serves as the foundation for the rest of the application. One application can consists of multiple product types. The total interest rate consists of an objective part based solely on hard information and an optional subjective adjustment based on available soft information. This optional adjustment is only allowed for some product types.

4. Sample Selection and Empirical Design

4.1. Sample selection

The sample for our main analyses consists of 2,600 credit applications from August 2013 through August 2014, including applications from both the small and medium-sized segment and the lower half of the corporate segment. A benefit of this data is that many of our variables are based on meta-data captured and logged by the information systems. In the field of auditing, it is preferred to audit these processes based on such meta-data because it provides an independent and unmanipulated source of data (Jans, Alles, and Vasarhelyi, 2013).

This set of applications is selected based on the following criteria. They are all from the same country. The applicant requests some form of credit (e.g., early repayment requests are excluded). The application must be for a meaningful amount (no administrative cases), and it must have available data for our key constructs. To ensure consistency throughout the sample, our main analyses focus on a sample of accepted applications.

4.2. Empirical design

Main dependent variable

Our main dependent variable is a proxy for the soft information integrated into the credit application. It is operationalized by means of using the subjective component of the interest rate. This optional subjective component is intended to adjust the interest rate margin that is calculated based on a set of hard information. Campbell et al. (2016) verify this role by documenting a significant link between their direct measure for soft information, based on textual analysis of exception reports, and the discretionary part of the interest rate. Both a positive (interest decreasing) and a negative (interest increasing) adjustment are possible. Our main dependent variable is a single quantitative construct defined below.[5]

$$(\text{Soft information} \mid \text{Taken into consideration}) = \frac{\text{Subjective adjustment}}{\text{Calculated interest margin}}$$

Note that we do not attempt to measure the amount of soft information. We are interested in measuring the degree of effectiveness with which soft information is integrated into the

[5]The height of the adjustment is correlated with the calculated interest margin. A large calculated interest margin generally requires a larger adjustment. We avoid hard information from indirectly affecting our soft information construct by using a ratio that explicitly corrects for the height of the calculated interest margin.

decision process. By doing so, we not only examine the gathering and sharing of soft information but also emphasize the aspect of appropriately acting on that information.[6]

We define "effectively integrating soft information" as using soft information to adjust the calculated interest rate toward an interest rate that better reflects the underlying probability of default. This definition implies that a higher interest-decreasing adjustment reflects an increase (decrease) in effectiveness if the calculated interest rate is substantially too high (low) and vice versa for a higher interest-increasing adjustment. As explained in Section 3.1, our sample of applications is characterized by a calculated interest rate that is typically overstated, compared to the underlying probability of default. As a result, we can interpret an average increase (decrease) in interest-reducing adjustments as soft information being integrated more (less) effectively into decision-making.[7]

Research design

We aim to isolate the effect on our soft information construct that is attributable to the organizational design shock. This is operationalized by the use of a differences-in-differences design. Our treatment group is the small and medium-sized business segment of the bank, and the corporate segment is our control group. These two segments have their own separate departments within the bank, each with their own employees, policies, and procedures. There is no reason to suspect that the policy change in the small and medium-sized department also effects applications for corporate clients. This assumption is strengthened by the observation that involvement of the risk department is already a general practice for the corporate segment throughout our sample period. The first set of empirical procedures is based on the following model (i indexes borrowers and t indexes months):

$$Soft\ information_i = \beta_0 + \beta_1 Shock_t + \beta_2 SME_i + \beta_3 Shock_t * SME_i + Controls + \epsilon_{i,t} \quad (1)$$

[6] It is for this reason that we do not look at the absolute value of our dependent variable; the absolute value would not allow us to study the effectiveness of incorporating soft information.

[7] Note that this interpretation is specific to our setting. In a scenario where the calculated interest rate is typically understating the underlying probably of default, the interpretation would be reversed.

The coefficient β_1 will be an indicator for the general trend of the control group. β_2 indicates any level differences of the trend in the ex ante period when comparing the control group with the treatment group. For our analysis, the main coefficient of interest is β_3, which indicates how the subjective adjustment is influenced by the shock, relative to the unaltered trend of the control group. A significant coefficient on the interaction term is consistent with our expectation that the shock has an effect on the way that soft information is integrated into the decision making process. A more interest decreasing correction, for our specific setting, should be interpreted as soft information being integrated into decision-making more effectively, as it allows to reverse the typically overstated calculated interest rate more. This interpretation comports with the work of Campbell et al. (2014) and Campbell et al. (2016), who study a similar setting. To summarize, a significantly positive β_3 coefficient supports hypothesis 2A (soft information incorporated more effectively), whereas a significantly negative β_3 coefficient supports of hypothesis 2B (soft information incorporated less effectively).

Control variables

Several control variables are added to account for applicant and application-specific factors. The internal risk rating captures the majority of applicant-specific factors. This rating is calculated based on the objective characteristics of an applicant that are available to the bank. The height of the rating corresponds with the estimated probability of default; a high rating relates to a high estimated probability of default. Bank employees often use the risk rating as baseline prediction for the riskiness of a company. We therefore expect that companies with a high rating will receive more attention and have more soft information taken into consideration. There are multiple types of rating models that are available for use, and the dummy variable *objective rating* indicates whether the risk rating is generated by a new stream of arguably better rating models. Two additional applicant-specific control variables are included: the dummy variable *going concern* is 1 if the applicant is still active six months after the application, and the dummy variable *easy financials* is 1 if basic financial information is available via the Chamber of Commerce. Three additional application specific control variables are included. *Variable interest* is a dummy variable to indicate whether the interest rate is variable, and *new credit* is a dummy variable to indicate that the application is a request for a new loan. The variable *processing time* is the number of working days between the initialization date and the date at which the application is either accepted or rejected.

Selection effects

Certain product types receive an interest rate that is only based on hard information. These standard products types are generally used for lower risk (e.g., lower credit amount) applications and allow for quick processing. The loan officer, however, influences this product choice and thus indirectly influences whether a subjective adjustment is possible. This presents a potential problem because our soft information construct is only available for applications where a subjective adjustment is possible. A potential solution would be to assume that the subjective adjustment is zero for those applications with a standard product type. This approach, however, would ignore any nonrandomness involved in selecting the product type for an application. The work by Heckman (1979) provides a better solution in the form of the Heckman selection model. This estimation procedures works by treating the selection effect as an omitted variable bias. An adjustment factor is estimated via a selection model, which is then included in the outcome model as an additional explanatory variable. In the first stage, the following selection model is estimated via binary choice estimation procedures:

$$\begin{aligned} Custom\ product_i = \beta_0 + \beta_1 Shock_t + \beta_2 SME_i + \beta_3 Shock_t * SME_i \\ + Controls + Exclusion\ restrictions + \epsilon_{i,t} \end{aligned} \tag{2}$$

Based on this first stage, an adjustment factor called the inverse Mills ratio or Lambda is calculated, which is included in the second stage as an additional explanatory variable:

$$\begin{aligned} Soft\ information_i = \beta_0 + \beta_1 Shock_t + \beta_2 SME_i + \beta_3 Shock_t * SME_i \\ + \beta_4 Lambda_t + Controls + \epsilon_{i,t} \end{aligned} \tag{3}$$

At least one valid exclusion restriction is required to assure econometric validity of the Heckman procedure. These exclusion restrictions have to be included in the selection equation but not in the outcome equation. It is difficult to find an exclusion restriction for which it makes economic sense to exclude it from the second-stage equation. For our situation, two reasonably valid exclusion restrictions have been identified: a dummy variable to indicate a limited liability company (LLC legal form) and the years of incorporation. Conversations with bank employees and policy documents suggest that the legal form of a company is an important consideration for choosing a particular product type. Both the age of an applicant and the legal form are hard information factors that are not expected to influence the subjective adjustment. To statistically verify this claim, the first set of analyses will include these inclusion restrictions to assess their significance in the second stage outcome equation.

5. Descriptive Statistics and Empirical Results

5.1. Descriptive Statistics

Table 1 provides detailed descriptive statistics for the samples used for our two main empirical tests. The first (second) column in Table 1 displays the mean values and standard deviations for the subset of observations with product types that can (cannot) have a subjective adjustment. For the total set of observations these statistics are displayed in the third column. Around 65% of the applications in our sample have a construction that allows for a subjective adjustment. This results in 1,646 applications for the custom product type and

917 observations for the standard product type, totaling up to 2,563 observations.

The dependent variable *subjective adjustment* is included in the first column of Table 1. On average, the subjective adjustment is -3.3% with a standard deviation of 23.3%. This negative adjustment indicates that an average application receives a subjective adjustment that increases its calculated interest rate by 3.3%. The standard deviation, however, implies that this adjustment varies substantially across applications. Around 60% of our 2,563 applications belong in the small and medium-sized treatment group. The group of applications with a standard product type consists mainly of these applicants. This is explained by corporate applicants generally requesting a larger credit amount, resulting in a custom credit construction. Roughly 60% of the observations fall in the ex-post period. Consistent with our prediction, applications with a standard product design have an, on average, lower risk rating and request a relatively small amount of credit. Over 95% of the applicants in our sample are still active at least six months after the application has been completed. The average applicant firm has an age of 22 years. A credit application with a potential adjustment generally takes 46 working days to complete, compared to 25 working days for those with a standard product design.

[Table 1 about here]

The main econometric characteristic of our empirical analyses is the differences-in-differences approach. We believe that we can improve our understanding of this approach if we support our analyses by splitting the descriptive statistics based on the four groups of the differences-in-differences design. In our case, that results in a split based on small and medium-sized businesses versus corporate and ex ante versus ex post. These descriptive statistics are displayed in Table 2 panel A for the first set of empirical tests and Table 2 panel B for the second set of empirical tests.

The main statistics of interest in Table 2 Panel A are the subjective adjustment differences between the four groups. The treatment group is small and medium-sized loan applications, and the control group is corporate loan applications. Before (after) indicates before (after) the policy change. In our control group, the subjective adjustment goes from -4.3% in the ex ante period to an average of -8.4% in the ex post period. This number deviates from the pattern present in the averages of the treatment group; a positive 1.4% in the ex ante period shifts to an average of 2.4%. The treatment group has a slightly higher risk rating, compared to the control group, and this implies that larger clients are, in general, given a lower estimated probability of default. These ratings do not appear to be affected by the shock. After the introduction of a risk approver, the average processing time for small and medium-sized loan applications increases from 32 working days to 37 working days.

[Table 2 Panel A about here]

Panel B of Table 2 is constructed using the same groups as Panel A. Of main interest is the distribution between custom and standard products types. The proportion of custom products for the treatment group slightly increases from 38% to 46%. This distribution remains at a high level throughout our sample period for the control group. There is a slight increase in the average credit amount and internal risk rating for the treatment group. Similar to Panel A, the average processing time for small and medium-sized loan applications increases with around seven working days.

[Table 2 Panel B about here]

5.2. Main Analysis

In Table 3, we show the results of our main differences-in-differences model. Three different specifications are included. Columns 1 and 4 show the results of our baseline model using only the explanatory variables of the differences-in-differences design. Columns 2 and 5 improve this baseline model by also including the control variables. The final columns 3 and 6 present the most comprehensive model by adding two-digit NAICS industry and geographical region indicators. We run an ordinary least squares estimation for the equations represented in the first three columns. Our dependent variable, however, is a ratio that is censored by an upper and lower bound of 2. Ordinary least squares estimation does not take such bounded dependent variables into account, and we therefore run a Tobit type 1 censored regression estimation in the final three columns. All estimation results have standard errors that are corrected for heteroscedasticity and clustered by two digit industry.

The results of Table 3 indicate that the interest adjustment of the control group has decreased (-0.044, p = 0.028) when comparing the ex ante situation with the ex post situation. Also consistent with the descriptive statistics of Table 2 Panel A is the positive and significant coefficient for SME (0.071, p = 0.007). The interaction term between *shock* and SME is significant and positive with a coefficient of around 5.0% (p = 0.034). This result provides support to our first hypothesis, stating that the introduction of a risk approver significantly influences the integration of soft information into credit applications. The positive sign of this coefficient indicates that the effectiveness of integrating soft information into decision-making improved, which supports hypothesis 2A. This result holds across all specifications and estimation methods. The *internal credit rating* (0.019, p = 0.000) and *credit amount* (0.001, p = 0.000) are significant and positive in all of our estimations. This result is consistent with our expectation that applications with a higher probability of default or those that request a higher credit amount receive more attention in the application process. Neither exclusion restriction, $LLC\ Legal\ Form$ (p = 0.543) nor $Years\ of\ incorporation$ (p = 0.197), is statistically significant.

The coefficient and significance of the interaction term is also influenced by the trend of the treated group, relative to the trend of the control group. This consideration is relevant even when the common trend assumption holds. In the descriptive statistics from panel A of Table 2, we show that the average subjective adjustment changes from 1.4% to 2.4% for the treatment group and from -4.3% to -8.4% for the control group. Under the common trend assumption, this indicates that, without the shock, the subjective adjustment for the treated group would have changed from 1.4% to approximately -2.7%. The interaction coefficient in the first column of Table 3 (0.051, p = 0.025) displays this differences between the expected -2.7% versus the observed 2.4%. Our result is strengthened by the fact that this difference is not only driven by a relative trend effect but also by an absolute increase in the mean value of our construct.

5.3. Selection Effects

Our main result may be driven by a selection effect. Loan officers can sort applications into loan proposals that allow for subjective interest adjustments (a "custom product") or ones that do not allow for such an adjustment (a "standard product"). This second set of analyses is therefore aimed at identifying how selection effects (changes in loan sorting) impact our results. First, we investigate whether the shock changed the selection behavior of the loan officer. Second, we investigate whether this selection behavior could be driving the results observed in the first set of empirical tests. The results of the selection equations presented in Table 4 aim at answering the first question. Table 5 presents the results of the outcome equations that replicate the results of Table 3 with a selection correction. Two estimation procedures for the Heckman selection model are included: a full information maximum-likelihood estimation (MLE) procedure and the less efficient two-step procedure. The two-step procedure has corrected standard errors to account for the fact that an estimated parameter is included in the second stage.

[Table 4 about here]

The main result of Table 4 is that the coefficient on the interaction term $shock * SME$ is not statistically significant (p-values range from 0.100 to 0.768) in the majority of specifications. This indicates that, from an econometric perspective, the shock did not trigger a change in selection behavior by the loan officers. Both exclusion restrictions are, as expected, significant determinants of the likelihood of being assigned a custom product type ($LLC\ Legal\ Form$: 0.242, p = 0.000 and $Years\ of\ incorporation$: 0.002, p = 0.001). Besides the main explanatory variables and the two exclusion restrictions, there are other control variables that are found to be significant in the selection equations. Applications with higher internal ratings (0.017, p = 0.000), ratings generated by the new rating models (0.043, p = 0.072), or applicants requesting a new loan (0.202, p = 0.000) have a higher likelihood of being assigned a custom product type.

[Table 5 about here]

Following the structure of Table 4, Table 5 includes two specifications and two estimation methods. The objective of Table 5 is to investigate whether the results in Table 3 are driven by a selection effect. An applicable starting point is to investigate the statistics generated by the Heckman estimation procedure: *rho* and *lambda*. *Rho* is calculated to assess whether selection into the outcome sample is based on a non-random process. At the bottom of Table 5, it becomes apparent that *rho* is significant (-0.755, p = 0.000) in most specifications, indicating that the selection into the outcome sample is not random. A negative *rho* indicates that the unobservable characteristics affect the likelihood of receiving a custom product in an opposite way compared to how these characteristics influence the height of the subjective adjustment. Both the estimates of *rho* and *lambda* indicate that selection into the outcome equation is not random, which makes it worthwhile to include *lambda* into the outcome equations.

As in Table 3, the main variable of interest in Table 5 is the interaction term $Shock * SME$. Throughout all specifications this interaction term remains positive and significant (p-values range from 0.020 to 0.069). The inclusion of a selection adjustment therefore does not compromise our earlier results. The increased effectiveness of incorporating soft information, as observed in Table 3, is not driven by a selection effect.

6. Additional Tests

6.1. *Loan officer Fixed Effects*

The amount of employees responsible for assessing and processing the applications in our sample is quite heterogeneous. There are roughly 350 different loan officers who have been identified as assigned to a credit application in our sample. Around 250 different risk approvers are identified as being involved with a credit application in our ex post sample. This heterogeneity in the loan officer pool makes it hard to implement loan officer fixed effects in our main analyses. In many cases, a loan officer only occurs once or twice in our sample.

[Table 6 about here]

Table 6 replicates Table 3 for a subsample of applications assigned to a loan officer that occurs at least twice in both the before and after period. The literature documents that employee turnover is one of the main drivers of changes in economic outcomes after a change in organizational design (e.g. Campbell, 2012). The goal of this analysis is therefore to study whether our main effect is driven by a shift in the loan officer pool and to check whether our results are susceptible to the inclusion of loan officer fixed effects. Columns 1 and 3 speak to this first question and show that the interaction term for this subsample remains statistically significant (0.059, $p = 0.012$). In the columns 2 and 4, loan officer fixed effects are included, and this absorbs the effect of SME but our interaction term $Shock * SME$ remains unchanged (0.056, $p = 0.032$). Overall, these results show that our main result is primarily driven by a change in behavior by the established loan officers and not by a change of the loan officer pool.

6.2. Loan outcomes

Our primary results in Table 3 and our additional results of Table 6 indicate a change in behavior by the loan officers following the change in organizational structure. These analyses, however, do not allow us to infer whether this change in behavior has positive or negative implications for the loan outcomes. The literature usually uses the charge-off rate to assess these loan outcomes. The first two columns of Table 7 show how the charge-off rate is influenced by the change in organizational structure. The dependent variable of these logit regressions is a dummy variable that equals 1 if the risk rating of a loan is higher than the charge-off threshold 15 months after the loan has been granted. Regardless of region and segment fixed effects, the primary coefficient of this regression is not significant (-0.002, $p = 0.966$ and -0.009, $p = 0.774$). This result is not surprising, given that the nature of these loans is long term and performance would be expected to deteriorate gradually. Given our sample years, it is not possible to directly observe the long-term charge-off outcome, but we use a proxy (the "probability of default slope") to approximate the long-term performance of these loans. This probability is calculated by estimating a linear regression for each loan where the risk rating (on a per-month basis) is the dependent variable and time (month relative to the date of loan granting) is the independent variable. This slope is then used as the dependent variable for the OLS regressions in columns 3 and 4 of Table 7. The negative coefficient on $Shock * SME$ (-0.047, $p = 0.030$ and -0.044, $p = 0.040$) suggests that, relative to the control group, the shock in organizational design improves the probability of default prospect. These results confirm that better integration of soft information into loan applications helps the performance of these loans.

[Table 7 about here]

6.3. *Pre-screening*

An aspect of the application process that is potentially relevant but hard to empirically investigate is pre-screening. Pre-screening does not relate to our main result directly because these screens are generally performed by a different set of employees. It is, however, helpful to provide some descriptive results that give insight into this pre-screening. We create a separate sample based on another information system that stores the majority of credit requests received by the bank via regular channels such as the internet or by telephone. Requests that lack the basic requirements and those that are retracted by the applicant are filtered out of this sample. Following the approach of Qian et al. (2015), we split the sample up into two periods, February 2013 through August 2013 and February 2014 through August 2014. For each period, an estimation is performed to identify how the known characteristics of an application influence the likelihood it will be allowed to enter the next stage of the application process. This approach is descriptive and not intended to differentiate between time trends or a potential effect attributable to our shock.

[Table 8 about here]

Table 8 provides the results of logit estimations for these two periods. A large difference between these two periods is the inflow of credit requests; it decreases from a total of 4,000 to around 1,600. This is consistent with the small and medium-sized business financing described by Wehinger (2014). Looking at the coefficients, there are several characteristics that indicate a higher likelihood of early acceptance: applications that received via a face-to-face meeting (*client meeting*: 0.262, p = 0.000), applicants who request a loan via their *relationship manager* (0.423, p = 0.000), and applicants whose existing loan is older than one year (*establish client*: 0.097, p = 0.000). The positive and significant coefficient on *going concern* (0.179, p = 0.000) confirms that pre-screening can select applicants that have a lower probability of defaulting within six months after the application is completed.

Besides the reduction in the number of requests, there are three other differences in Table 8 when comparing between the two periods. The first is the increasing importance of the credit amount that is requested. Consistent with the trend of increasing risk aversion by the bank is the lower likelihood of an *early acceptance* for higher credit amounts in the more recent period (0.012, p = 0.082 → -0.030, p = 0.000). It is possible for the front office to request a brief early recommendation by the risk department, which is included by the dummy variable *risk involvement*. A strong increase in the coefficient for risk involvement is observed when comparing between the two periods (0.302, p = 0.000 → 0.763, p = 0.000). This growth suggests the risk department also has an increased importance during the pre-screening stages after the organizational shock. The final difference is an increase in the explanatory power ($R^2 = 0.175 \rightarrow R^2 = 0.446$) of these basic characteristics, which highlights the attempt of the bank to improve the loan review process for small to medium-sized companies.

7. Robustness Tests

7.1. Likelihood of acceptance

In the previous empirical tests, only accepted applications were considered. As mentioned by Agarwal and Hauswald (2010), leaving these unaccepted applications out of the sample might result in an endogeneity problem. The goal of this section is to investigate whether the main results are driven by the exclusion of these non-accepted applications and whether the shock influenced the likelihood of acceptance itself. We define non-accepted applications as those that have a completed application process but are rejected or declined at the final stage.

[Table 9 about here]

The first column of Table 9 is a reduced version of the model underlying Table 3. Around 300 non-accepted applications are added to the sample, and the dummy variable *accepted* indicates whether an application is accepted. The negative and significant coefficient (-0.024, p = 0.019) of *accepted* shows that accepted applications, on average, receive a more interest-increasing or less interest-decreasing adjustment compared to non-accepted applications. The interaction coefficient remains unchanged (0.050, p = 0.029), which gives reassurance that our results are not driven by the exclusion of non-accepted applications.

Columns 2 through 5 of Table 9 present logit estimations with the *acceptance* dummy as the dependent variable. Columns 4 and 5 are based only on the small and medium-sized business sample, due to an insufficient number of non-accepted observations with a standard product type for the control group. The results, as displayed through the negative and significant *shock* coefficient (-0.058, p = 0.001), are consistent with a downward trend in the likelihood of acceptance. The interaction term is insignificant (0.029, p = 0.397), indicating that the likelihood of acceptance is not impacted by the introduction of a risk approver.

7.2. Common Trend Assumption

Our analyses contain two differences-in-differences estimations, each with their own common trend assumption. There is no actual test that guarantees a robust verdict on the assumption of the common trend. There are, however, several tests that can give some reassurance that a violation of the common trend assumption is not driving the results (Roberts and Whited, 2012). We will present two of these tests: a graphical representation of the ex ante linear trend and a placebo tests using a random shock on the ex ante sample.

The graphical approach is performed by estimating a linear trend via OLS for the ex ante period. These estimates result in a linear prediction line for both the treatment and control groups. While this approach does not represent a statistical procedure, it does allow for an eyeball approach to identify potential problems. These graphical results are followed up by placebo tests designed to add statistical verification. The intuition behind this test is that a randomly picked placebo shock point in the ex ante period should not yield a significant interaction term if the common trend assumption holds.[8] A number of random placebo shock

[8] The ex ante period used is Sept. 1, 2013, through Nov. 30, 2013, excluding December 2013, to avoid

dates are picked and the baseline specifications, presented below, are iteratively estimated based on these placebo shocks. The results of these iterations are averaged to yield the final results.

$$Soft\ information_i = \beta_0 + \beta_1 Placebo\ Shock_t + \beta_2 SME_i + \beta_3 Placebo\ Shock_t * SME_i$$

$$Custom\ product_i = \beta_0 + \beta_1 Placebo\ Shock_t + \beta_2 SME_i + \beta_3 Placebo\ Shock_t * SME_i$$

Figure 1 and Panel A of Table 10 display the test results for the first set of analyses. Inspection of Figure 1 for both the small and medium-sized and corporate samples shows a decreasing trend that appears to be aligned between the two groups. The placebo results presented in panel A of Table 10 confirm the common trend suggested by Figure 1; the placebo shock interaction term is not significant (-0.001, p = 0.810).

[Figure 1 about here]

[Table 10 Panel A about here]

Figure 2 and Panel B of Table 10 display the test results for the second set of analyses. Figure 2 reveals an almost flat trend for the corporate segment, while there appears to be an increasing trend for the small and medium-size segment. This would suggest that these trends are misaligned. The nonsignificant (-0.449, p = 0.308) interaction term in panel B of Table 10, however, counteracts with this suggestion. Comparison of the rear end of the small and medium-sized linear trend line with the mean value in panel B of Table 2 (46%) suggests that the increasing trend of the segment discontinues after the shock. We confirm this suggestion when we plot the ex post period selection trend. In Figure 3, we indeed observe that both trends appear to be aligned for the ex post period. This observation results in a special econometric case where the interaction term in Table 4 is mainly influenced by any trend difference that has preceded the shock. This intuition is best understood by the

potentially picking up effects related to the shock.

fact that switching the 0-1 around for the shock term will yield identical results to Table 4 but with flipped signs. The nonsignificance of the interaction term in Table 4 therefore indicates that the common trend assumption is not violated. Overall, these results indicate that the common trend assumption can reasonably be expected to hold for both the outcome model and the selection model.

[Figure 2 about here]

[Table 10 Panel B about here]

[Figure 3 about here]

8. Conclusions

We examine how the allocation of decision rights affects the generation, sharing, and application of soft information in a large European bank. Our research design is built on a differences-in-differences model that uses the introduction of a risk approver as a quasi-natural experiment. Using a sample of loan applications, we find that reallocating decision rights to a higher organizational level affects the integration of soft information into the assessment of credit applications. Decreasing the decision authority of loan officers leads them share their soft information with the risk approvers. Introducing risk management therefore improves the banks decision-making by allowing soft information to be better used in the assessment of credit applications. This increased effectiveness is accompanied by an improvement in the loan outcomes. These findings are robust to controlling for strategic loan-sorting behavior, manager fixed effects, and the likelihood of acceptance. We also document that this improved integration of soft information is driven by a change in behavior of the loan officers and not by a change in the loan officer pool.

The results of our study contradict with recent findings of Qian, et al. 2015 and Liberti (2017). However, the results are consistent with the findings of Campbell (2012) who shows that newly appointed loan officers have better skills than incumbent loan officers to decide on who should be granted a loan and at which conditions. Incumbent loan officers were inclined to hold on to previous regulation to assure they were making the right decision. In our paper we examine a situation where central management decided to take away the decision rights from the loan officers to make the call on whether loan applicants will be granted a loan or not. Based on the findings of Qian, et al. 2015 and Liberti (2017) one would expect that decision making would deteriorate. However, in the case we describe central management can justify its decision as the regulator imposes on the bank that they develop and implement tighter internal controls to assure that loans are granted to the right applicants under the appropriate conditions. The justification makes it more likely that loan officers understand and subscribe to the decision of the bank to appoint central risk approvers. In the extent they subscribe to the conditions they are more likely to cooperate with central management to implement the new decision structure (Fehr and Gchter, 2000). The evidence we show would suggest that this cooperation extends to loan officers stepping up their effort to collect information in the wake of the centralization decision.

Due to data limitations, it is hard to empirically determine what precisely is driving our result that centralization improves the effective use of soft information in lending decisions. There are, however, several characteristics of our bank that have been documented to influence the relationship between organizational design and the use of soft information. The first relates to market competition between banks, as our bank operates in a setting with much market competition. The analytical model of Heider and Inderst (2012) yields the expectation that the agency problem between a bank and its loan officers is bigger in situations of high competition, causing the loan officer to rely primarily on hard information and neglect soft information. Furthermore, Canales and Nanda (2012) empirically document that decentralization can have adverse effects on the lending terms for small businesses in settings with high competition. The introduction of a risk approver might therefore help alleviate this heightened agency problem and allow for soft information to be integrated better into the application process. Second, Berger, Miller, Petersen, Rajan, and Stein (2005) show that bigger banks have more trouble incorporating soft information in loan reviews. Our bank is one of the biggest in Europe. Reducing its decentralization might thus help alleviate its difficulties with incorporating soft information in lending. Lastly, loan officers and risk managers are relatively homogeneous in our setting. It is common for risk managers to have been in the position of loan officers previously. Canales and Greenberg (2016) document, for example, that it is easier for loan officers with similar lending styles to transfer information between each other. This homogeneity may help reduce some of the frictions that might prevent soft information from being transferred, enabling the introduction of a risk approver to improve the use of soft information.

There are several other limitations to this study that could be addressed by future research. Our sample period is relatively short. Future research can extend on our work by investigating how the influence of risk management evolves over a longer period. Additionally, besides a reallocation of design rights, the bank is trying to improve its risk rating models by shifting employees focus to verifiable information. While these new risk rating models do not affect our sample period, they do provide an interesting avenue for future research.

References

Abernethy, M., Bouwens, J., van Lent, L., 2004. Determinants of control system design in divisionalized firms. The Accounting Review 79, 545–570.

Agarwal, S., Hauswald, R., 2010. Distance and Private Information in Lending. Review of Financial Studies 23, 2757–2788.

Aghion, P., Tirole, J., 1997. Formal and Real Authority in Organizations. Journal of Political Economy 105, 1–29.

Berg, T., 2015. Playing the Devil's Advocate: The Causal Effect of Risk Management on Loan Quality. Review of Financial Studies 28, 3367–3406.

Berg, T., Puri, M., Rocholl, J., 2014. Loan officer incentives, internal ratings and default rates. Working Paper .

Berger, A. N., Klapper, L. F., Udell, G. F., 2001. The Ability of Banks to Lend to Informationally Opaque Small Businesses. Journal of Banking & Finance 25, 2127–2167.

Berger, A. N., Miller, N. H., Petersen, M. A., Rajan, R. G., Stein, J. C., 2005. Does function follow organizational form? Evidence from the lending practices of large and small banks. Journal of Financial Economics 76, 237–269.

Bolton, P., Dewatripont, M., 1994. The Firm as a Communication Network. Quarterly Journal of Economics 109, 809–839.

Campbell, D., 2012. Employee Selection as a Control System. Journal of Accounting Research 50, 931–966.

Campbell, D., Epstein, M. J., Martinez-Jerez, F., 2011. The learning effects of monitoring. Accounting Review 86, 1909–1934.

Campbell, D., Erkens, D. H., Loumioti, M., 2014. Exception Reports as a Source of Idiosyncratic Information. Working Paper .

Campbell, D., Erkens, D. H., Loumioti, M., 2016. Monitoring and the Portability of Soft Information. Working Paper .

Canales, R., Greenberg, J., 2016. A Matter of (Relational) Style: Loan Officer Consistency and Exchange Continuity in Microfinance. Management Science 62, 1202–1224.

Canales, R., Nanda, R., 2012. A darker side to decentralized banks: Market power and credit rationing in SME lending. Journal of Financial Economics 105, 353–366.

Cole, S., Kanz, M., Klapper, L., 2015. Incentivizing Calculated Risk-Taking: Evidence from an Experiment with Commercial Bank Loan Officers. Journal of Finance 70, 537–575.

Constant, D., Kiesler, S., Sproull, L., 1994. What's mine is ours, or is it? A study of attitudes about information sharing. Information Systems Research 5, 400–421.

Crawford, V. P., Sobel, J., 1982. Strategic Information Transmission. Econometrica 50, 1431–1451.

Dessein, W., 2002. Authority and Communication in Organizations. The Review of Economic Studies 69, 811–838.

Dewatripont, M., Tirole, J., 2005. Modes of Communication. Journal of Political Economy 113, 1217–1238.

Drexler, A., Schoar, A., 2014. Do Relationships Matter? Evidence from Loan Officer Turnover. Management Science 60, 2722–2736.

Gibbons, R., Henderson, R., 2012. What Do Managers Do? Exploring Persistent Performance Differences among Seemingly Similar Enterprises. In: *The Handbook of Organizational Economics*, Princeton University Press, pp. 680–731.

Heckman, J., 1979. Sample Selection Bias as a Specification Error. Econometrica 47, 153–161.

Heider, F., Inderst, R., 2012. Loan Prospecting. Review of Financial Studies 25, 2381–2415.

Hertzberg, A., Liberti, J. M., Paravisini, D., 2010. Information and incentives inside the firm: Evidence from loan officer rotation. Journal of Finance 65, 795–828.

Holmström, B., Milgrom, P., 1990. Regulating Trade Among Agents. Journal of Institutional and Theoretical Economics pp. 85–105.

Holmström, B., Milgrom, P., 1991. Multitask principal-agent analyses: Incentive contracts, asset ownership, and job design. Journal of Law, Economics, & Organization pp. 24–52.

Jans, M., Alles, M., Vasarhelyi, M., 2013. The case for process mining in auditing: Sources of value added and areas of application. International Journal of Accounting Information Systems 14, 1–20.

Jensen, M. C., Meckling, W. H., 1992. Specific and General Knowledge, and Organizational Structure. In: Werin, L., Wijkander, H. (eds.), *Contract Economics*, Blackwell Publishers, Oxford, U.K.

Liberti, J. M., Mian, A. R., 2009. Estimating the Effect of Hierarchies on Information Use. Review of Financial Studies 22, 4057–4090.

Lin, H., 2007. Effects of extrinsic and intrinsic motivation on employee knowledge sharing intentions. Journal of Information Science 33, 135–149.

Milgrom, P. R., Roberts, J., 1992. Economics, organization, and management. Prentice-Hall.

Moers, F., 2006. Performance Measure Properties and Delegation. The Accounting Review 81, 897–924.

Mosk, T., 2014. Delegation of Authority and Information Manipulation: Evidence from Bank Lending Decisions. Working Paper .

Petersen, M. A., 2004. Information: Hard and Soft. Working Paper .

Qian, J. Q., Strahan, P. E., Yang, Z., 2015. The Impact of Incentives and Communication Costs on Information Production and Use: Evidence from Bank Lending. Journal of Finance 70, 1457–1493.

Raith, M., 2008. Specific knowledge and performance measurement. The RAND Journal of Economics 39, 1059–1079.

Roberts, M. R., Whited, T. M., 2012. Endogeneity in Empirical Corporate Finance. Working Paper .

Uchida, H., Udell, G. F., Yamori, N., 2012. Loan officers and relationship lending to SMEs. Journal of Financial Intermediation 21, 97–122.

Wehinger, G., 2014. SMEs and the credit crunch. OECD Journal: Financial Market Trends 2013/2, 115–148.

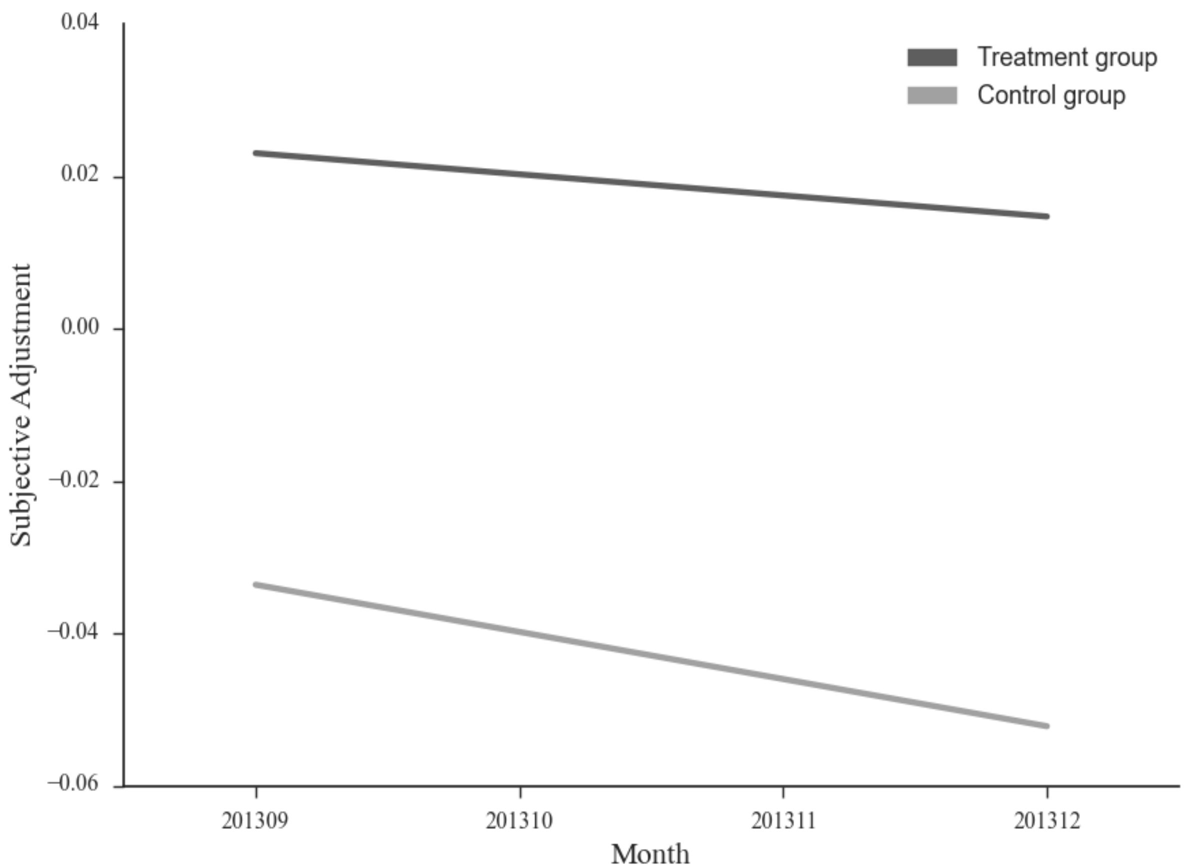

Fig. 1. Ex-ante trend for the main analysis.

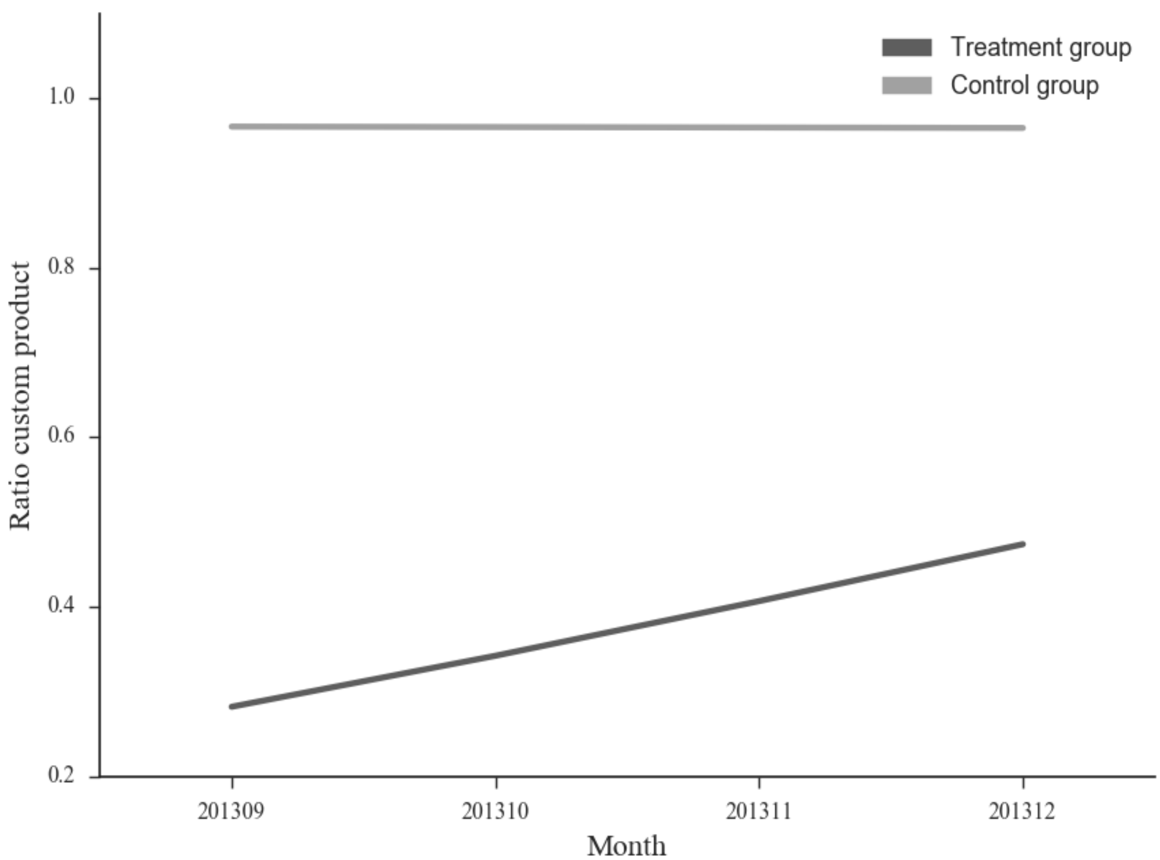

Fig. 2. Ex-ante trend for the selection analysis.

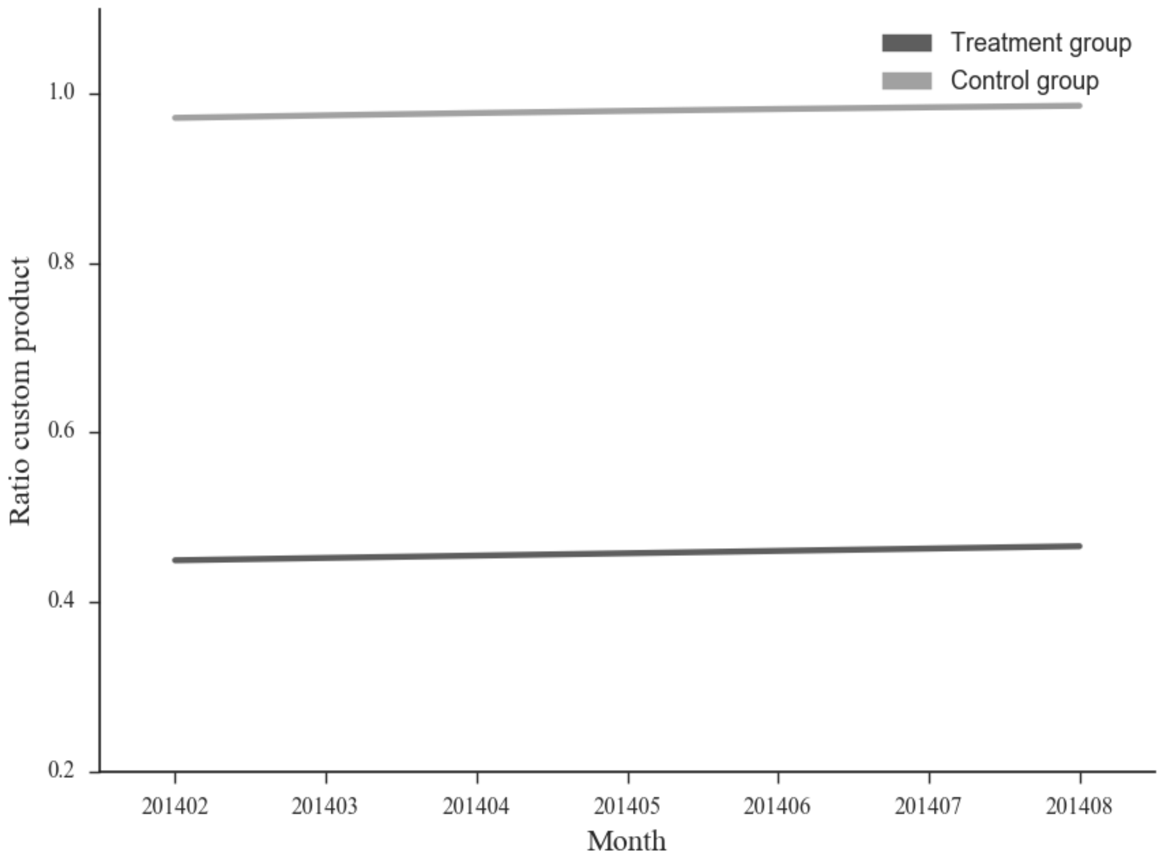

Fig. 3. Ex-post trend for the selection analysis.

Table 1: Descriptive Statistics

	Custom products	Standard products	Total	Min	Max
SME	0.397 (0.489)	0.971 (0.169)	0.602 (0.489)	0.000	1.000
Shock	0.601 (0.490)	0.538 (0.499)	0.579 (0.494)	0.000	1.000
Subjective Adjustment	−0.033 (0.233)			−1.857	1.000
Custom product			0.642 (0.479)	0.000	1.000
Variable Interest	0.606 (0.489)	0.692 (0.462)	0.637 (0.481)	0.000	1.000
Internal Rating	13.270 (3.254)	12.797 (3.035)	13.100 (3.185)	5.000	22.000
Going Concern	0.976 (0.152)	0.979 (0.143)	0.977 (0.149)	0.000	1.000
LLC Legal Form	0.759 (0.428)	0.347 (0.476)	0.612 (0.487)	0.000	1.000
Objective rating	0.758 (0.428)	0.708 (0.455)	0.740 (0.439)	0.000	1.000
Years of incorporation	24.065 (24.447)	18.267 (19.563)	21.991 (22.984)	1.000	312.000
Processing time	45.603 (38.631)	25.062 (22.649)	38.254 (35.194)	1.000	195.000
New credit	0.501 (0.500)	0.301 (0.459)	0.429 (0.495)	0.000	1.000
Amount	8.676 (17.924)	0.842 (6.160)	5.873 (15.295)	0.003	193.339
Easy financials	0.717 (0.451)	0.314 (0.464)	0.573 (0.495)	0.000	1.000
Observations	1,646	917	2,563	2,563	2,563

This table presents the descriptive statistics for the variables described in Section 4. The first column shows the subset of observations with a credit construction that allows for an adjustment. The second column is the subsample with a credit construction that does not allow for an adjustment. The third column is the total sample. *SME* is 1 for SME clients and 0 for corporate clients (treatment group indicator). *Shock* is 1 for applications after the policy change (after the shock). *Subjective Adjustment* is our main dependent variable and proxies for soft information, calculated by: (Subjective interest rate adjustment / Calculated interest margin). Note, a negative adjustment increases the interest rate. *Variable Interest* is 1 for applications assigned a variable interest rate. *Going Concern* is 1 if the applicant did not default within 6 months after the application. *Objective rating* is 1 if an improved rating model is used. *Processing time* is the number of workings days from initiation to completion. *New credit* is 1 if the applicant requests a new loan and 0 in case of a loan increase or an overdraft loan. *Amount* is the total credit amount requested in euros scaled by a random number. *Easy financials* is 1 if basic financial information is available at the Chamber of Commerce. Standard deviations are included in brackets.

Table 2A: Descriptive Statistics

	Before		After	
	Treated	Control	Treated	Control
Subjective Adjustment	0.014	−0.043	0.024	−0.084
	(0.150)	(0.264)	(0.116)	(0.282)
Variable Interest	0.412	0.781	0.406	0.705
	(0.493)	(0.414)	(0.492)	(0.457)
Internal Rating	13.283	13.378	13.315	13.158
	(3.115)	(3.246)	(3.168)	(3.378)
Going Concern	0.972	0.970	0.985	0.976
	(0.165)	(0.170)	(0.121)	(0.153)
LLC Legal Form	0.712	0.791	0.658	0.828
	(0.454)	(0.407)	(0.475)	(0.378)
Objective rating	0.692	0.783	0.720	0.795
	(0.463)	(0.413)	(0.449)	(0.404)
Years of incorporation	22.504	24.490	22.807	25.304
	(23.950)	(23.676)	(22.075)	(26.624)
Processing time	31.744	51.704	36.938	53.261
	(24.366)	(48.735)	(25.717)	(40.316)
New credit	0.636	0.387	0.639	0.427
	(0.482)	(0.488)	(0.481)	(0.495)
Amount	2.421	12.142	2.315	13.329
	(3.118)	(22.214)	(2.581)	(21.872)
Easy financials	0.632	0.764	0.614	0.792
	(0.483)	(0.425)	(0.487)	(0.406)
Observations	250	406	404	586

This table presents the descriptive statistics for the sample underlying our first set of analyses. The columns are split based on the groups of the differences-in-differences model. The treatment group are SME loan applications and the control group are corporate loan applications. Before (After) indicates before (after) the policy change. *Subjective Adjustment* is our main dependent variable and proxies for soft information, calculated by: (Subjective interest rate adjustment / Calculated interest margin). Note, a negative adjustment increases the interest rate. *Variable Interest* is 1 for applications assigned a variable interest rate. *Going Concern* is 1 if the applicant did not default within 6 months after the application. *Objective rating* is 1 if an improved rating models is used. *Processing time* is the number of workings days from initiation to completion. *New credit* is 1 if the applicant requests a new loan and 0 in case of a loan increase or an overdraft loan. *Amount* is the total credit amount requested in euros scaled by a random number. *Easy financials* is 1 if basic financial information is available at the Chamber of Commerce. Standard deviations are included in brackets.

Table 2B: Descriptive Statistics

	Before		After	
	Treated	Control	Treated	Control
Custom product	0.379	0.964	0.456	0.980
	(0.486)	(0.186)	(0.498)	(0.140)
Variable Interest	0.592	0.765	0.567	0.699
	(0.492)	(0.425)	(0.496)	(0.459)
Internal Rating	12.889	13.316	13.093	13.193
	(3.075)	(3.244)	(3.089)	(3.389)
Going Concern	0.971	0.971	0.985	0.977
	(0.167)	(0.167)	(0.120)	(0.151)
LLC Legal Form	0.481	0.796	0.475	0.829
	(0.500)	(0.404)	(0.500)	(0.376)
Objective rating	0.684	0.774	0.730	0.793
	(0.465)	(0.419)	(0.444)	(0.406)
Years of incorporation	19.407	24.599	20.493	25.219
	(21.063)	(23.598)	(21.090)	(26.492)
Processing time	24.244	52.128	32.149	52.958
	(21.015)	(48.868)	(24.713)	(40.250)
New credit	0.420	0.397	0.451	0.430
	(0.494)	(0.490)	(0.498)	(0.495)
Amount	1.153	12.127	1.277	13.474
	(2.189)	(22.045)	(2.018)	(22.570)
Easy financials	0.429	0.770	0.437	0.793
	(0.495)	(0.422)	(0.496)	(0.406)
Observations	659	421	885	598

This table presents the descriptive statistics for the sample underlying our second set of analyses. The columns are split based on the groups of the differences-in-differences model. The treatment group are SME loan applications and the control group are corporate loan applications. Before (After) indicates before (after) the policy change. *Custom product* is our second dependent variable and indicates whether an application was assigned a credit construction that allows for a subjective adjustment. *Variable Interest* is 1 for applications assigned a variable interest rate. *Going Concern* is 1 if the applicant did not default within 6 months after the application. *Objective rating* is 1 if an improved rating models is used. *Processing time* is the number of workings days from initiation to completion. *New credit* is 1 if the applicant requests a new loan and 0 in case of a loan increase or an overdraft loan. *Amount* is the total credit amount requested in euros scaled by a random number. *Easy financials* is 1 if basic financial information is available at the Chamber of Commerce. Standard deviations are included in brackets.

Table 3: Main Results

	Subjective Adjustment					
	OLS			Tobit [-2, 2]		
Shock	-0.041^{*}	-0.037^{**}	-0.044^{**}	-0.041^{**}	-0.037^{**}	-0.044^{**}
	(0.020)	(0.018)	(0.018)	(0.020)	(0.018)	(0.018)
SME	0.057^{***}	0.081^{***}	0.071^{***}	0.057^{***}	0.081^{***}	0.071^{***}
	(0.021)	(0.023)	(0.023)	(0.021)	(0.023)	(0.023)
Shock * SME	0.051^{**}	0.045^{**}	0.050^{**}	0.051^{**}	0.045^{**}	0.050^{**}
	(0.021)	(0.021)	(0.022)	(0.021)	(0.021)	(0.021)
Variable Interest		0.020	0.026		0.020	0.026
		(0.018)	(0.017)		(0.018)	(0.017)
Internal Rating		0.018^{***}	0.019^{***}		0.018^{***}	0.019^{***}
		(0.003)	(0.003)		(0.003)	(0.003)
Going Concern		−0.010	0.004		−0.010	0.004
		(0.029)	(0.024)		(0.029)	(0.024)
LLC Legal Form		−0.016	−0.016		−0.016	−0.016
		(0.025)	(0.026)		(0.025)	(0.025)
Objective rating		−0.002	0.001		−0.002	0.001
		(0.010)	(0.009)		(0.010)	(0.009)
Years of incorporation		0.0002	0.0002		0.0002	0.0002
		(0.0002)	(0.0001)		(0.0002)	(0.0001)
Processing time		0.0001	0.0001		0.0001	0.0001
		(0.0001)	(0.0001)		(0.0001)	(0.0001)
Easy financials		0.012	0.012		0.012	0.012
		(0.024)	(0.026)		(0.024)	(0.026)
New credit		−0.002	0.005		−0.002	0.005
		(0.014)	(0.016)		(0.014)	(0.016)
Amount		0.001^{***}	0.001^{***}		0.001^{***}	0.001^{***}
		(0.0002)	(0.0002)		(0.0002)	(0.0002)
Intercept	-0.043^{**}	-0.309^{***}	-0.321^{***}	−0.043	-0.309^{***}	-0.321^{***}
	(0.021)	(0.069)	(0.071)	(0.044)	(0.069)	(0.070)
Region indicators	No	No	Yes	No	No	Yes
Segment indicators	No	No	Yes	No	No	Yes
Observations	1,646	1,646	1,646	1,646	1,646	1,646
R^2	0.038	0.113	0.157			
Adjusted R^2	0.037	0.106	0.135			
Log Likelihood				95.980	162.816	203.996

This table presents our main result, the effect of reallocating decision rights on the amount of soft information that is integrated into the assessment of a credit application. *Subjective Adjustment* is our main dependent variable and proxies for soft information, calculated by: (Subjective interest rate adjustment / Calculated interest margin). Note, a negative adjustment increases the interest rate. *SME* is 1 for SME clients and 0 for corporate clients (treatment group indicator). *Shock* is 1 for applications after the policy change (after the shock). *Shock * SME* is the main variable of interest, this interaction term indicates how the reallocation of decision rights affects the amount of considered soft information. *Variable Interest* is 1 for applications assigned a variable interest rate. *Going Concern* is 1 if the applicant did not default within 6 months after the application. *Objective rating* is 1 if an improved rating model is used. *Processing time* is the number of workings days from initiation to completion. *New credit* is 1 if the applicant requests a new loan and 0 in case of a loan increase or an overdraft loan. *Amount* is the total credit amount requested in euros scaled by a random number. *Easy financials* is 1 if basic financial information is available at the Chamber of Commerce. Standard errors are included in brackets. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Table 4: First Stage Heckman Selection Model

	Likelihood Custom Product			
	Maximum Likelihood		Two-Step	
LLC Legal Form	0.227***	0.183***	0.237***	0.242***
	(0.052)	(0.028)	(0.049)	(0.049)
Years of incorporation	0.001**	0.002***	0.001***	0.002***
	(0.001)	(0.001)	(0.0005)	(0.001)
Shock	0.081	0.119***	0.064	0.078
	(0.055)	(0.043)	(0.052)	(0.052)
SME	−0.581***	−0.543***	−0.567***	−0.522***
	(0.069)	(0.061)	(0.042)	(0.043)
Shock * SME	−0.037	−0.072*	−0.017	−0.028
	(0.052)	(0.044)	(0.056)	(0.057)
Variable Interest	−0.003	−0.055	−0.006	−0.040
	(0.063)	(0.044)	(0.039)	(0.040)
Internal Rating	0.019***	0.009*	0.017***	0.017***
	(0.004)	(0.005)	(0.003)	(0.004)
Going Concern	−0.110***	−0.087*	−0.117	−0.117
	(0.042)	(0.052)	(0.074)	(0.076)
Objective rating	0.053*	0.026	0.058**	0.043*
	(0.029)	(0.026)	(0.024)	(0.024)
Processing time	0.002***	0.001***	0.002***	0.002***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Easy financials	0.025	0.107***	0.027	0.062
	(0.053)	(0.038)	(0.048)	(0.048)
New credit	0.238***	0.152***	0.252***	0.202***
	(0.060)	(0.048)	(0.039)	(0.039)
Amount	0.001	0.001	0.002	0.001
	(0.003)	(0.004)	(0.001)	(0.001)
Intercept	0.022	0.364	0.002	−0.031
	(0.422)	(0.479)	(0.341)	(0.420)
Region and Industry indicators	No	Yes	No	Yes
Robust Clustered SE	Yes	Yes	No	No
log pseudolikelihood	−812.539	−678.257		
Observations	2,563	2,563	2,563	2,563

This table presents the results for the first stage of the Heckman selection procedure. The results indicate whether the shock had an effect on the selection behavior of loan officers. The dependent variable *Custom product* is 1 if an application was assigned a credit construction that allows for a subjective adjustment. The first two columns are estimated using full-information maximum likelihood and the last two columns are estimated by the less efficient two-step approach. Two exclusion restrictions are included that are not included in the second stage: *LLC Legal Form* and the *Years of incorporation*. *SME* is 1 for SME clients and 0 for corporate clients (treatment group indicator). *Shock* is 1 for applications after the policy change (after the shock). *Shock * SME* is the main variable of interest, this interaction term indicates how the shock altered the selection behavior of loan officers. *Variable Interest* is 1 for applications assigned a variable interest rate. *Going Concern* is 1 if the applicant did not default within 6 months after the application. *Objective rating* is 1 if an improved rating model is used. *Processing time* is the number of workings days from initiation to completion. *New credit* is 1 if the applicant requests a new loan and 0 in case of a loan increase or an overdraft loan. *Amount* is the total credit amount requested in euros scaled by a random number. *Easy financials* is 1 if basic financial information is available at the Chamber of Commerce. All coefficients (except the intercept) are average marginal effects. Standard errors are included in brackets. *p<0.1; **p<0.05; ***p<0.01

Table 5: Second Stage Heckman Selection Model

	Subjective Adjustment			
	Maximum Likelihood		Two-Step	
Shock	-0.035^{*}	-0.049^{***}	-0.036^{**}	-0.046^{***}
	(0.020)	(0.017)	(0.014)	(0.014)
SME	0.009	0.175^{***}	0.057^{*}	0.095^{***}
	(0.028)	(0.031)	(0.032)	(0.027)
Shock * SME	0.052^{**}	0.038^{*}	0.048^{**}	0.048^{**}
	(0.022)	(0.021)	(0.023)	(0.022)
Variable Interest	0.018	0.031^{**}	0.020	0.027^{*}
	(0.022)	(0.012)	(0.016)	(0.016)
Internal Rating	0.020^{***}	0.015^{***}	0.019^{***}	0.019^{***}
	(0.003)	(0.003)	(0.002)	(0.002)
Going Concern	−0.018	0.017	−0.013	0.006
	(0.027)	(0.028)	(0.036)	(0.036)
Objective rating	0.004	−0.003	0.001	0.002
	(0.010)	(0.010)	(0.013)	(0.013)
Processing time	0.0002	−0.0002	0.0001	0.00001
	(0.0001)	(0.0001)	(0.0002)	(0.0001)
Easy financials	0.028	-0.050^{***}	0.009	−0.010
	(0.020)	(0.012)	(0.016)	(0.017)
New credit	0.024	-0.035^{**}	0.006	−0.004
	(0.018)	(0.015)	(0.018)	(0.017)
Amount	0.001^{***}	0.001^{***}	0.001^{***}	0.001^{***}
	(0.0002)	(0.0002)	(0.0003)	(0.0003)
Intercept	-0.373^{***}	-0.194^{***}	-0.329^{***}	-0.294^{***}
	(0.075)	(0.061)	(0.058)	(0.068)
Region and Industry indicators	No	Yes	No	Yes
Robust Clustered SE	Yes	Yes	No	No
rho	0.459	−0.755	0.152	−0.195
rho Prob > chi2	0.0^{***}	0.0^{***}		
lambda	0.104	−0.174	0.033	−0.042
lambda SE	0.018^{***}	0.023^{***}	0.039	0.034
log pseudolikelihood	−812.539	−678.257		
Observations	1,646	1,646	1,646	1,646

This table presents the results for the second stage of the Heckman selection procedure. The results indicate whether the resuls of Table 3 are affected by a selection effect. *Subjective Adjustment* is our main dependent variable and proxies for soft information, calculated by: (Subjective interest rate adjustment / Calculated interest margin). Note, a negative adjustment increases the interest rate. The first two columns are estimated using full-information maximum likelihood and the last two columns are estimated by the less efficient two-step approach. *SME* is 1 for SME clients and 0 for corporate clients (treatment group indicator). *Shock* is 1 for applications after the policy change (after the shock). *Shock * SME* is the main variable of interest, this interaction term indicates how the reallocation of decision rights affects the amount of considered soft information. *Variable Interest* is 1 for applications assigned a variable interest rate. *Going Concern* is 1 if the applicant did not default within 6 months after the application. *Objective rating* is 1 if an improved rating model is used. *Processing time* is the number of workings days from initiation to completion. *New credit* is 1 if the applicant requests a new loan and 0 in case of a loan increase or an overdraft loan. *Amount* is the total credit amount requested in euros scaled by a random number. *Easy financials* is 1 if basic financial information is available at the Chamber of Commerce. Standard errors are included in brackets. *p<0.1; **p<0.05; ***p<0.01.

Table 6: Loan Officer Fixed-Effects

	Subjective Adjustment			
	OLS		Tobit [-2, 2]	
Shock	-0.046^{**}	-0.036^{**}	-0.046^{***}	-0.044^{***}
	(0.018)	(0.017)	(0.018)	(0.016)
SME	0.054^{***}	0.027	0.054^{***}	0.049^{**}
	(0.021)	(0.084)	(0.021)	(0.024)
Shock * SME	0.059^{**}	0.056^{**}	0.059^{**}	0.060^{**}
	(0.023)	(0.026)	(0.023)	(0.027)
Variable Interest	0.021	0.046^{**}	0.021	0.030
	(0.018)	(0.021)	(0.018)	(0.019)
Internal Rating	0.021^{***}	0.023^{***}	0.021^{***}	0.022^{***}
	(0.002)	(0.003)	(0.002)	(0.002)
Going Concern	0.001	-0.053	0.001	-0.007
	(0.036)	(0.040)	(0.035)	(0.046)
Objective rating	-0.001	-0.0001	-0.001	-0.002
	(0.016)	(0.020)	(0.016)	(0.015)
Processing time	0.0001	-0.0001	0.0001	0.00004
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Easy Financials	0.006	0.0001	0.006	0.004
	(0.017)	(0.021)	(0.017)	(0.017)
New credit	0.005	0.029^{*}	0.005	0.014
	(0.019)	(0.017)	(0.018)	(0.018)
Amount	0.001^{***}	0.001^{***}	0.001^{***}	0.001^{***}
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Intercept	-0.365^{***}	-0.323^{***}	-0.365^{***}	-0.364^{***}
	(0.071)	(0.084)	(0.069)	(0.081)
Loan Officer FE	No	Yes	No	Yes
Region + Industry indicators	Yes	Yes	Yes	Yes
Group Stats	Total: 150	Min: 2	Mean: 8.4	Max: 39
R-Square	0.173	0.299		
Observations	1,213	1,213	1,213	1,213

This table presents the results of an analysis designed to investigate how changes in the loan officer pool and loan officer fixed-effects affect our main results. *Subjective Adjustment* is our main dependent variable and proxies for soft information, calculated by: (Subjective interest rate adjustment / Calculated interest margin). Note, a negative adjustment increases the interest rate. *SME* is 1 for SME clients and 0 for corporate clients (treatment group indicator). *Shock* is 1 for applications after the policy change (after the shock). *Shock * SME* is the main variable of interest, this interaction term indicates how the reallocation of decision rights affects the amount of considered soft information. *Variable Interest* is 1 for applications assigned a variable interest rate. *Going Concern* is 1 if the applicant did not default within 6 months after the application. *Objective rating* is 1 if an improved rating model is used. *Processing time* is the number of workings days from initiation to completion. *New credit* is 1 if the applicant requests a new loan and 0 in case of a loan increase or overdraft loan. *Amount* is the total credit amount requested in euros scaled by a random number. *Easy financials* is 1 if basic financial information is available at the Chamber of Commerce. Standard errors are included in brackets. *p<0.1; **p<0.05; ***p<0.01.

Table 7: Loan outcome analysis

	Likelihood of Charge-Off		Probability of Default slope	
Shock	0.013	0.018	0.015	0.015
	(0.018)	(0.015)	(0.012)	(0.013)
SME	-0.076	-0.054	-0.008	-0.001
	(0.046)	(0.044)	(0.010)	(0.012)
Shock * SME	-0.002	-0.009	-0.047**	-0.044**
	(0.037)	(0.033)	(0.020)	(0.020)
Variable Interest	0.159***	0.163***	-0.020**	-0.017*
	(0.025)	(0.026)	(0.008)	(0.009)
Processing time	-0.001***	-0.001***	0.00002	0.00004
	(0.0003)	(0.0003)	(0.0001)	(0.0001)
Easy financials	-0.047**	-0.027	0.028***	0.032***
	(0.020)	(0.023)	(0.007)	(0.009)
New credit	-0.099***	-0.099***	-0.020**	-0.018*
	(0.030)	(0.024)	(0.010)	(0.009)
Amount	-0.001*	-0.001	0.0003	0.0003
	(0.001)	(0.001)	(0.0002)	(0.0002)
Intercept	-1.272***	-0.476	0.043***	0.006
	(0.467)	(0.626)	(0.012)	(0.037)
Model	Logit	Logit	OLS	OLS
Region and Segment FE	No	Yes	No	Yes
(Pseudo) R-Squared	0.116	0.150	0.024	0.053
Observations	1,661	1,661	1,661	1,661
Log Likelihood	-724.694	-695.834		

This table presents the results of an analysis designed to investigate how the observed change in behavior by loan officers following the change in organizational design influences the ex-post loan outcomes. *Likelihood of Charge-Off* is our first dependent variable and is 1 if the credit rating is above the charge-off threshold 15 months after the loan is granted. *Probability of Default slope* is our second dependent variable and is calculated by estimating a linear regression for each loan where the risk rating is the dependent variable and time is the independent variable. *SME* is 1 for SME clients and 0 for corporate clients (treatment group indicator). *Shock* is 1 for applications after the policy change (after the shock). *Shock * SME* is the main variable of interest, this interaction term indicates how the reallocation of decision rights affects the amount of considered soft information. *Variable Interest* is 1 for applications assigned a variable interest rate. *Processing time* is the number of workings days from initiation to completion. *New credit* is 1 if the applicant requests a new loan and 0 in case of a loan increase or overdraft loan. *Amount* is the total credit amount requested in euros scaled by a random number. *Easy financials* is 1 if basic financial information is available at the Chamber of Commerce. Standard errors are included in brackets. *p<0.1; **p<0.05; ***p<0.01.

Table 8: Screening analysis

	Likelihood early acceptance (Logit)			
	2013-2 – 2013-10		2014-2 – 2014-10	
Log(Amount)	0.010	0.012^{*}	-0.029^{***}	-0.030^{***}
	(0.007)	(0.007)	(0.004)	(0.005)
Client meeting	0.266^{***}	0.262^{***}	0.222^{***}	0.215^{***}
	(0.033)	(0.033)	(0.034)	(0.035)
Relationship Manager	0.420^{***}	0.423^{***}	0.303^{***}	0.302^{***}
	(0.029)	(0.031)	(0.028)	(0.031)
Established client	0.096^{***}	0.097^{***}	0.106^{**}	0.099^{**}
	(0.026)	(0.026)	(0.045)	(0.044)
Risk involvement	0.305^{***}	0.302^{***}	0.772^{***}	0.763^{***}
	(0.028)	(0.029)	(0.073)	(0.061)
Years of incorporation	0.001	0.001	0.0001	−0.00000
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
LLC Legal Form	0.068^{***}	0.061^{***}	−0.035	−0.036
	(0.020)	(0.023)	(0.026)	(0.029)
Going Concern	0.175^{***}	0.179^{***}	0.336^{**}	0.340^{**}
	(0.044)	(0.042)	(0.160)	(0.159)
Intercept	-3.095^{***}	-3.023^{***}	-3.706^{***}	-2.739^{***}
	(0.298)	(0.369)	(0.942)	(0.876)
Region and Industry indicators	No	Yes	No	Yes
Pseudo R-squared	0.158	0.175	0.433	0.446
log pseudolikelihood	-2340.163	-2291.762	-544.078	-531.46
Observations	4,062	4,062	1,563	1,563

This table presents the descriptive results of an analysis designed to investigate how pre-screening behavior at the early stages changes over time. The first two columns are applications from the period 2013-02 to 2013-10, the last two columns are applications from the period 2014-02 to 2014-10. *Early acceptance* is the dependent variable which indicates whether an application made it past the initial pre-screening stage. *Client meeting* is 1 if a face-to-face meeting took place. *Relationship Manager* is 1 if the application entered the system via a relationship manager. *Established client* is 1 if the client is older than 1 year and has a prior credit history with the bank. *Risk involvement* is 1 if a brief early recommendation was requested from the risk department. *Going Concern* is 1 if the applicant did not default in the 6 months after the application was completed. *log(Amount)* is the logarithmic transformation of the credit amount in euros. All coefficients (except intercept) are average marginal effects. Standard errors are included in brackets. *p<0.1; **p<0.05; ***p<0.01.

Table 9: Likelihood of acceptance analysis

	Subjective Adjustment	Likelihood of acceptance Custom product	Standard product
Accepted	-0.024^{**}		
	(0.009)		
Shock	-0.049^{***}	-0.058^{***}	0.008
	(0.017)	(0.018)	(0.030)
SME	0.055^{***}	-0.040	
	(0.019)	(0.026)	
Shock * SME	0.050^{**}	0.029	
	(0.021)	(0.034)	
Internal Rating	0.019^{***}	0.004^{***}	0.002
	(0.003)	(0.001)	(0.004)
Objective rating	0.004	0.001	-0.026
	(0.008)	(0.020)	(0.023)
New credit	-0.006	0.031^{**}	-0.040
	(0.012)	(0.015)	(0.025)
Amount	0.001^{***}	-0.0003	0.027
	(0.0002)	(0.0003)	(0.027)
Intercept	-0.259^{***}	2.789^{***}	1.278^{**}
	(0.055)	(0.480)	(0.571)
Model	OLS	Logit	Logit
(Pseudo) R-Squared	0.149	0.040	0.027
Observations	1,982	1,945	1,085
Log Likelihood	-707.270	-494.110	

This table presents the results of an analysis designed to investigate whether the shock influenced the likelihood of acceptance. The first column replicates Table 3 but includes applications that are not accepted or declined at the final stage back into the sample. *Subjective Adjustment* is our main dependent variable and proxies for soft information, calculated by: (Subjective interest rate adjustment / Calculated interest margin). Note, a negative adjustment increases the interest rate. *SME* is 1 for SME clients and 0 for corporate clients (treatment group indicator). *Shock* is 1 for applications after the policy change (after the shock). *Shock * SME* is the main variable of interest, this interaction term indicates how the reallocation of decision rights affects the amount of considered soft information. *Objective rating* is 1 if an improved rating model is used. *New credit* is 1 if the applicant requests a new loan and 0 in case of a loan increase or an overdraft loan. *Amount* is the total credit amount requested in euros scaled by a random number.

All coefficients (except the intercept) are average marginal effects. Standard errors are included in brackets. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Table 10A: Placebo Test

	Dependent variable:
	Subjective Adjustment OLS Dif-in-Dif with random placebo shock
Placebo Shock	−0.013
	$p = 0.584$
SME	0.058
	$p = 0.032^{**}$
Placebo Shock * SME	−0.001
	$p = 0.810$
Intercept	−0.035
	$p = 0.085^{*}$
Observations	656
Note:	*p<0.1; **p<0.05; ***p<0.01 For an explanation of this procedure see Section 7. The results are the average coefficients and p values of the following amount of iterations: 30

Table 10B: Placebo Test

	Dependent variable:
	Custom product Probit Dif-in-Dif with random placebo shock
Placebo Shock	0.033
	$p = 0.345$
SME	−2.347
	$p = 0.000^{***}$
Placebo Shock * SME	0.449
	$p = 0.308$
Intercept	1.885
	$p = 0.000^{***}$
Observations	1,080
Note:	*p<0.1; **p<0.05; ***p<0.01 For an explanation of this procedure see Section 7. The results are the average coefficients and p values of the following amount of iterations: 30