Essays in Financial Intermediation

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Zusammenfassung

Die vorliegende Arbeit untersucht drei unabhängige Fragestellungen auf dem Gebiet der Finanzintermediation.

Kreditanalysten der drei weltweit führenden Rating-Agenturen stehen in der ersten Studie im Zentrum der Untersuchung. Die empirische Analyse konzentriert sich auf die organisationsinterne Neubesetzung von Kreditanalysten in ihrer beobachtenden sowie untersuchenden Rolle von Emittenten. Insbesondere interessiert uns dabei, welchen Einfluss solcherlei personelle Wechsel auf die Bonitätseinstufung von Emittenten haben. Diesen organisatorischen Veränderungen wird in der andauernden kritischen Auseinandersetzung mit Rating-Agenturen wenig Beachtung geschenkt. Die Ergebnisse zeigen einerseits: Finden Neubesetzungen von Analysten statt, steigt die Wahrscheinlichkeit, dass Bonitätseinstufungen geändert werden. Übergreifend betrachtet zeichnet sich allerdings ein nur geringfügiger Effekt auf die Bonitätseinstufungen per se ab. Unsere Erkenntnisse sind für Gesetzesentscheidungen zu Rotationsvorschriften von Bedeutung.

In der zweiten Studie untersuchen wir die Treiber der Finanzierungskosten von Privatplatzierungen. Anhand der Beleuchtung dieser Thematik tragen wir deren gestiegener Bedeutung infolge von Kreditverknappung und quantitativen Lockerungsmaßnahmen innerhalb der Geldpolitik Rechnung. Die Fragestellung, ob Informationsasymmetrien zwischen Kreditgebern und Kreditnehmern die Finanzierungskosten beeinflussen, steht dabei im Fokus. Unsere empirischen Analysen ergeben, dass Informationsasymmetrien mit höheren Risikoaufschlägen einhergehen. Diese Erkenntnisse sind zum einen für Entscheidungen von Investoren und Emittenten von Privatplatzierungen relevant. Zum anderen leisten wir einen Beitrag zur Ausgestaltung von politischen Maßnahmen, die darauf abzielen, Refinanzierungsoptionen für den privaten Sektor zu erweitern.

Die dritte Studie kann als Ausgangspunkt für zukünftige Untersuchungen des Einflusses ortsbezogener sozialer Medien auf den Finanzdienstleistungssektor angesehen werden. Ich betrachte hierbei, welche Auswirkungen Konsumentenbewertungen von Bankfilialen auf die dort getätigten Spareinlagen haben. Die Daten eines weit verbreiteten sozialen Online-Netzwerkes dienen als Basis der Analyse. Es lässt sich eine robuste Korrelation dieser Faktoren erkennen: Höhere Bewertungen sind mit höheren Wachstumsraten der Spareinlagen von Bankfilialen assoziiert. In weitergehenden Analysen kann ein kausaler Zusammenhang hingegen nicht bestätigt werden. Meine Erkenntnisse stehen im Kontext der andauernden Debatte zu Chancen und Risiken von sozialen Medien sowie deren Regulierung. Sowohl Banken als auch gesetzgebende Stellen können daraus einen entscheidungsrelevanten Nutzen ziehen.

Abstract

This thesis encompasses three independent studies related to the subject of financial intermediation.

In the first study, we explore the credit analyst coverage of corporate debt issuers at the three leading credit rating agencies. In particular, we empirically assess whether analyst changes have an influence on credit ratings. In light of the continued criticism of credit rating agencies, the role of analyst changes might have been overlooked. We demonstrate that analyst changes are associated with increased rating change activism. At the same time, we find that the effect on credit ratings per se is limited. Our results inform legislation mandating analyst rotation as a legal requirement.

The second study investigates the role of information asymmetry between borrowers and lenders with regard to the cost of non-bank private placements of debt. Such debt instruments have gained momentum in periods of a credit crunch and quantitative easing in monetary policy. We utilize several measures of information asymmetry. Empirical results reveal higher costs of debt incurred by opaque issuers as compared to their more transparent counterparts. These findings are of relevance for corporate financing decisions as well as policy initiatives attempting to broaden the sources of private sector refinancing.

The third study pioneers research on the effects of mainstream location-based social media on the financial services sector. I determine whether consumer ratings of bank branches in a major online social network have an effect on the growth of branch deposits. I conclude that higher consumer ratings are linked to higher deposit volume growth in terms of correlation. Whereas further empirical analysis shows that this is not a causal effect. My findings relate to decision-making not only for bank management but also for legislators in the debate about social media and its potential opportunities and caveats.

Analyst changes and credit ratings

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Abstract

We investigate the effect of credit analyst changes on long-term ratings of S&P 500 issuers between 2002 and 2015. We find that analyst changes are associated with a higher probability of rating changes. Analyst changes are also associated with lower credit ratings. However, this lowering effect is limited in terms of economic magnitude. Our results empirically inform policies requiring mandatory credit analyst rotation.

Keywords: *Rating agencies, credit ratings, credit analysts, rotation policy, analyst bias*
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I. Introduction

In the aftermath of the financial crisis of 2008/2009, the European Parliament and Council targeted analysts of credit rating agencies ("CRAs") specifically with increased regulation (cf. E.U. Commission (2009)). Analyst changes in issuer coverage after four to seven years depending on the CRA analyst's role were introduced as a mandatory requirement. The regulator's response is rooted in the criticism that CRAs had not lowered their ratings in a timely manner in the course of the financial crisis. The new rules are intended to "correct those failures" by improving credit rating decisions (European Parliament, Council of the European Union (2009), p.2).

The above-mentioned criticism prompted the CRAs to emphasize several counterarguments. Not only did they stress the role of reputation when it comes to clients and investors putting their trust into the CRAs' service. CRAs also emphasized their structured credit rating processes as a means to attain objectivity in their credit rating decisions. Moreover, CRAs aim to limit the influence potentially induced by individual CRA analysts by requiring committee-based ratings decisions. One of the "big three" rating agencies, Fitch, even ceased publishing press releases quoting CRA analysts' statements, the purpose of which was to underscore the importance of institutional opinions as opposed to analyst opinions. Given the opposing perspectives put forth by the regulators and the CRAs, the impact of CRA analyst changes on credit ratings remains opaque.

In our paper, we study the effect of analyst changes on both the probability of rating changes and the level of long-term issuer ratings[1]. Rating levels and changes thereof have been shown to profoundly impact issuers' cost of debt (e.g., Kisgen and Strahan (2010); Kliger and Sarig (2000)). If the analyst change is of secondary order, as argued by the CRAs, we would expect no impact on subsequent rating actions. We focus on corporate ratings of Standard & Poor's 500 Index ("S&P 500") issuers published by the three leading rating agencies (Fitch, Moody's and Standard and Poor's ("S&P")) between 2002 and 2015. Based on a hand-collected dataset of 17,500 press releases and other publications by the CRAs, we assemble a timeline of CRA analyst coverage as well as rating actions.

Our main findings are as follows: First, the likelihood of rating changes increases by approximately 7 p.p.[2] in a quarter subsequent to analyst changes. The average probability amounts to approximately 5% suggesting that this result is economically significant. Our second finding shows that long-term issuer credit ratings turn out approximately 0.03 rating classes lower on the rating scale from 1-21[3] subsequent to analyst changes. This implies that credit ratings change both in downward and upward directions leading to a limited magnitude of effect on the rating level, on average. These results are stable after controlling for financial fundamentals as well as firm and time fixed effects.

The contribution of our study is threefold. First, we add to the existing literature on the behavior of CRAs. Theoretical models by Skreta and Veldkamp (2009) and Bolton et al. (2012) point toward conflicts of interest and biases in ratings by CRAs. Prior to this,

[1]Long-term issuer ratings and probability of rating actions are frequently analyzed outcomes in extant literature on CRAs, e.g., Lugo et al. (2015) or Mählmann (2011).

[2]Percentage points.

[3]For instance, "AAA" is one rating class. Cf. rating scale in Table A-IV in the Appendix.

Devenow and Welch (1996) had summarized theoretical approaches from other fields and their relevance to herding of CRAs in particular. Tests of these theoretical predictions are performed by Güttler and Wahrenburg (2007) and Mählmann (2011) who examine biases in credit ratings and relationship benefits. Further publications (see Güttler (2011), Lugo et al. (2015) and Dilly and Mählmann (2016)) provide evidence for herding among CRAs in ratings and inflated ratings during boom periods. Jaggi and Tang (2015) introduce another aspect, namely "soft" information (p.155) due to geographical distance between the CRA and the issuer, and show its relevance for credit ratings.

Our contribution goes beyond the entity level of CRAs by scrutinizing a deeper organizational layer: credit rating analysts. In addition to the above-mentioned drivers of credit ratings, we investigate the influence of analyst changes as another driver beyond financial fundamentals.

Work by Cornaggia et al. (2016), Fracassi et al. (2016) and Kisgen et al. (2016) has opened a stream of research dedicated to CRA analysts. These studies are related to the theoretical model specific to CRA analysts which was put forth by Bar-Isaac and Shapiro (2011). The said model is tested by Cornaggia et al. (2016) as well as Jiang et al. (2018). These authors extend the "revolving doors" literature dealing with CRA analyst job changes from CRAs to issuers and document ratings inflation prior to the job change. Another paper by Kisgen et al. (2016) investigates the determinants of analyst job promotions. Fracassi et al. (2016) also scrutinize the role of CRA analysts. The authors find that CRA analyst aggregate effects influence debt pricing. Sizable importance is attributed by these studies to CRA analysts beyond the influence of rating committees.

To the best of our knowledge, analyst changes and differentiated lead and secondary CRA analyst effects are not addressed in the literature. We are able to analyze analyst changes based on our daily and role-specific observations of analyst coverage. We therefore add to the literature by examining internal analyst changes within CRAs.

Finally, a set of papers has reviewed other types of financial analysts such as loan officers. Similar to CRA analysts, loan officers are tasked with creating transparency regarding entities, to the benefit of investors. A theory developed by Holmstrom (1982) regarding moral hazard reduction through loan officer coverage changes relates to the findings of Hertzberg et al. (2010). The authors infer that internal credit risk ratings tend to be more informative when loan officers face a re-assignment. The possibility of their own analysis lapses being uncovered by their successors appears to be an incentive for loan officers to judge more carefully. Further to coverage changes, the way loan officers process loan-related information has been investigated by Cole et al. (2015) and Berg et al. (2013). Qian et al. (2015) deal with effects of regulation and Liberti and Mian (2009) test the influence of organizational structure. One common finding of these contributions is an influence of rotation and other organizational factors on the loan rating process. Moreover, loan officers face adverse agency incentives which coverage changes seem to mitigate.

This motivates our study which is the first work to extend knowledge regarding the behavior of loan officers to CRA analyst changes and their impact on credit ratings. By doing so, we shed light on the motivation behind recently imposed regulation relating to

CRA analyst rotation (cf. E.U. Commission (2009)).

The remainder of this paper is organized as follows: Section II describes the institutional environment of CRAs. Section III presents our data. Empirical results are reported in Section IV. Section V concludes.

II. Institutional environment

The market position of CRAs has been closely linked to the growth of corporate debt securities issued. According to the Bank for International Settlements (2019), global debt securities of financial and non-financial corporations outstanding amounted to more than USD 24 trillion at the end of 2018. Monitoring debtors and providing transparency on their creditworthiness is a key task performed centrally as a professional service by CRAs. Despite being subject to criticism (Lugo et al. (2015); Efing and Hau (2015)) and additional regulation in the aftermath of the financial crisis of 2008/2009, the "big three" CRAs (Fitch, Moody's and S&P) still hold a market share of over 85% (SEC (2016)) in the United States. Fitch has the lowest market share (15%) while Moody's and S&P both hold around 35% each.

Besides general research services, the CRAs mainly assign ratings regarding creditworthiness and probability of default to issuers overall, to specific debt instruments (issues) and to structured products. The issuer's overall creditworthiness receives a rating prior to the rating of specific debt instruments of the same issuer (Standard & Poor's (2014)). Specific debt instrument ratings (e.g., for particular issues such as bonds) are based on these analyses. These specific ratings are only modified, should instrument-related factors such as terms and conditions, collateral or subordination require to deviate from the long-term issuer rating.

Rating processes of Fitch, Moody's and S&P exhibit no major discrepancies (cf. Fitch Ratings (2016); Moody's Investors Service (2017); Standard & Poor's (2014, 2017)). The sequence includes the following steps: the process usually starts with an issuer commissioning a credit rating. As the next step, a team comprised of a lead and a secondary analyst is assigned to the issuer and starts the analytical work by requesting rating-relevant information and data such as financial statements or reports from the issuer. The main role performed by the CRA analyst team consists of synthesizing this information into a credit opinion. The lead analyst oversees the analytical work which is primarily carried out by the secondary analyst. Moreover, the lead analyst is responsible for handling the relationship with the issuer[4]. It is crucial to point out that the coverage responsibility of analysts may change over time (Fitch Ratings (2016)). The reasons for analyst changes can be manifold including team capacity changes, availability of expertise, resignations by CRA analysts or sick leave. According to discussions with practitioners, analyst changes do not follow a standardized procedure.

The next step in the rating process is a meeting between the CRA analysts and the issuer's management team including on-site visits. After the management meeting, the

[4]The commercial part of relationship management has been separated from the credit rating process at most CRAs to avoid internal conflicts of interest.

CRA analysts will derive a credit rating recommendation. To a large extent, the said recommendation based on qualitative factors besides financial information. These primarily include business risk (e.g., industry risk, competitive position or country risk) and financial risks (e.g., leverage) and other factors (e.g., governance, policies and capital structure) of the issuer (Standard & Poor's (2014)). The recommendations help preparing the final decision taken by the "rating committee". During this meeting, the rating committee reviews rating recommendations by the analysts and assigns ratings. According to official statements by the big three CRAs, this part of the rating process is "central to analytical quality" (Standard & Poor's (2017), p.2). The committee's decision comprises several analysts including the lead analyst presenting his or her recommendation, a committee chairperson ensuring compliance with internal procedures and independent "outsider" analysts. Once the rating decision has been made in the rating committee, it is communicated to the issuer and the press release is aligned regarding factual correctness.

The credit rating process concludes with the publication of the press release and related rating information in the online portals of the CRAs. In case the rating coverage is active, a rating decision is followed by continuous monitoring of the issuer's credit quality. As a result, the CRA analysts typically remain in contact with the team on the issuer's side. The entire initial rating process takes between four to eight weeks to complete. The process is shorter in case of follow-up ratings.

With regard to European Union regulation on mandatory CRA analyst rotation (Regulation (EC) No. 1060/2009 as of 16th of September 2009, cf. European Parliament, Council of the European Union (2009)), this directive has been introduced in response to the global financial crisis. It applies to CRAs with more than 50 employees. Article 7(4) mandates that "a CRA shall establish an appropriate gradual analyst rotation mechanism with regard to the rating analysts [...]" (p.12). Specifically, according to Section C, point 8, maximum permissible coverage periods are explicitly determined for each CRA analyst role. Lead analysts should not cover an issuer for longer than four consecutive years. There is a maximum duration of five years for secondary analysts and seven years for the committee chairperson. For all roles, a "cooling period" of two years is mandatory before re-assuming coverage of an issuer. While the application of this regulation has been confirmed by Fitch, Moody's and S&P in principle, the implementation must be considered fragmented. The year of implementation might vary between European Union member states and there are exemption rules for some countries and CRAs[5].

Even though this regulation does not directly apply to the sample of this study focusing on United States issuers, it suggests that analyst changes are considered by regulators as one way to enhance the quality of credit ratings.

[5]For example, at Fitch: "As provided for within the E.U. Regulation, Fitch maintains an exemption from applying these [analyst change] requirements [...] for practical reasons such as language considerations" (Fitch Ratings (2018), p.18).

III. Data

A. Sample construction

We obtain the ratings history of S&P 500 index constituents from Bloomberg including rating changes and the type of rating action[6]. Following Güttler (2011) and Fracassi et al. (2016), we focus on long-term issuer ratings[7]. The sample includes a long-term ratings history from 2002 until 2015. Our sample consists of 460 companies of which 317 companies are covered by Fitch, 444 by Moody's and 449 by S&P, respectively[8].

We hand-collect the CRA analyst information from press releases, announcements, research reports and other publications available on the online portals of Fitch and Moody's. For S&P, these files are retrieved from the RatingsDirect module in S&P's Capital IQ platform[9]. CRA analyst data includes their name, status of lead or secondary analyst in their coverage team[10] and their location enabling us to track the coverage over time. Coverage is assumed to start at the first appearance of a CRA analyst on a report and to last until the first appearance of the succeeding CRA analyst[11]. This provides the tenure of each individual CRA analyst with an issuer. Overall, approximately 17,500 files were processed in order to construct the CRA analyst timeline for all three CRAs[12].

Lastly, control variables are downloaded from Bloomberg and S&P's Capital IQ and supplemented to the ratings and CRA analyst timeline via ticker symbols.

B. Descriptive statistics

B.1. Ratings history

The frequency of rating actions is one of our two outcome variables and shown in Panel A of Table I. We observe a comparable number of downgrades and upgrades per issuer overall for all three CRAs. Issuers covered by Fitch experience on average 1.60 downgrades as compared to Moody's (1.38) and S&P (1.36). For upgrades, very similar values prevail for both mean and median. The maximum values are 9 downgrades and 8 upgrades per issuer. In line with existing literature, the long-term issuer default ratings in our sample appear rather stable over time (Altman and Rijken (2004)).

[6]For Fitch and Moody's, we cross-check this history (accessed in April 2016) with information from their online portals. Regarding S&P, the rating history from Compustat is used for a cross check.

[7]In the case of Moody's, the corporate family rating (CFR) or senior unsecured rating is used if a long-term issuer rating was not assigned. The CFR is practically identical to the long-term issuer rating and mostly assigned to sub-investment grade issuers. For a few issuers, the CFR was withdrawn at some point, typically when an issuer had reached an investment grade rating. In these cases, the senior unsecured rating is also used instead.

[8]Due to missing data, e.g., on CRA analysts, for some firms (specifically, 11 firms rated by Fitch and 4 firms rated by Moody's) were removed from the raw sample.

[9]Formerly known as Global Credit Portal.

[10]Secondary analyst status was excluded for S&P since the majority of reports did not provide this distinction in a consistent manner.

[11]Due to limited availability of information before 2002, the coverage of all CRA analysts at the beginning of the sample period is assumed to begin in 2002. Our results are not sensitive to the choice of time frames.

[12]A related study by Fracassi et al. (2016) is based on a lower number of files in relation to the number of companies in the sample. The authors analyzed 26 reports per company whereas we include 38 reports per company in the sample. We were also able to provide finer granularity since our dataset entails a daily frequency and a longer scope ending in 2015. Furthermore, the distinction between lead and secondary analyst is important for the internal mechanisms at CRAs as outlined above and therefore accounted for only in our study.

The rating level is our second outcome variable. As far as the average rating level in our sample is concerned, firms have a rating of approximately 8.3 (Panel B of Table I). This equates to BBB+ (Baa1) at Fitch and S&P (Moody's) according to the rating scale in Table A-IV in the Appendix. All three CRA subsamples have the same median rating of 8. Hence, the average firm in our sample holds an investment grade rating which is approximately 3 rating classes above the sub-investment grade ratings beginning at BB+. Panel C reveals a similar pattern with regard to the magnitude of rating changes (conditional on change) for all three CRAs. Both the average as well as the median values suggest that ratings typically change to the next neighboring rating class, i.e., the magnitude amounts to approximately 1. Only at the upper 5th percentile, figures exhibit higher values. The maximum rating change magnitude amounts to four rating classes which is consistent across all three CRAs. Rating changes do not appear to exhibit large swings across the rating scale, on average.

- Table I about here: Rating level and rating changes -

Figure I presents the probability of rating downgrades and upgrades for all three CRAs over the observation period per year. It is defined as the share of firms experiencing a rating change. We observe that the rating actions reflect the overall economic development and the financial crisis in particular. The probability of downgrades widely exceeds the number of upgrades during the U.S. recession in 2002/2003 following the dot-com bubble in 2000/2001. During the subsequent recovery and boom period of the United States economy between 2004 and 2006, upgrades are more likely than downgrades. A peak level of rating changes is observed during the financial crisis of 2008/2009 which is mainly driven by downgrades. Following the recovery period after the financial crisis, the CRAs also adjust their actions. The probability of upgrades exceeds that of rating downgrades. This time-variant dependency of rating actions undertaken by CRAs in our data sample is confirmed by existing work[13]. In our regression analysis in Section IV we incorporate this dependency by controlling for time fixed effects.

- Figure I about here: Rating changes over time -

B.2. CRA analyst coverage timeline

The explanatory variable for our multivariate analyses, analyst change, is a binary variable equal to 1 if the credit rating of a firm has changed in a quarter and 0 otherwise[14]. In Table I (Panel D), the average figures for lead analysts of 1.77 changes (Fitch), 2.14

[13]For example, Bolton et al. (2012) and Bar-Isaac and Shapiro (2011) from a theoretical perspective, whereas Croce et al. (2011), Bangia et al. (2002) and Dilly and Mählmann (2016) state empirical evidence.

[14]Our sample includes 255 (Fitch), 283 (Moody's) and 332 (S&P) unique CRA analysts (the figure for S&P refers to the number of lead analysts only. Secondary analyst status was excluded for S&P since the majority of reports did not provide this distinction in a consistent manner) These figures are in line with studies by Fracassi et al. (2016) and Kisgen et al. (2016) who arrive at similar values. Moreover, we were able to derive their gender based on name searches in other online sources such as Bloomberg Executive Profiles and LinkedIn. Approximately one third of CRA analysts in our sample are female. Regarding location, Moody's is covering S&P 500 issuers purely out of their New York office while Fitch is based both in New York and Chicago. S&P serves its clients out of several additional office locations in the United States. Yet, for all three CRAs, New York is the most important office location.

changes (Moody's) and 2.31 changes (S&P) suggest more changes at Moody's and S&P while median figures for lead analyst changes are identical.

Figure II presents the probability of lead analyst changes per year. It is defined as the share of firms experiencing a lead analyst change. Fitch, Moody's and S&P exhibit similar overall trends. Following a steady increase in the probability of CRA analyst changes between 2002 and 2004, the level stagnates or drops until 2007. In 2007, all three CRAs surpass prior probability levels. During the financial crisis of 2008/2009, the level drops at Fitch and Moody's but remains stable at S&P. In the years 2010-2012, we observe a period of diverging patterns. From 2013-2015, the probability of lead analyst changes is increasing at all three CRAs.

- Figure II about here: Analyst changes over time -

Figure III shows descriptive evidence for the probability of rating changes per quarter defined as the share of firm-quarters exhibiting a rating change. Prior to lead analyst changes, we observe a lower probability compared to the quarters following analyst changes. This applies to the first and second quarter in particular. Subsequently, the probability of rating changes decreases. We do not observe major differences in this pattern for downgrades and upgrades. Also, both of these rating actions occur with the same likelihood. In Section IV, we will study this relationship in a multivariate framework.

- Figure III about here: Rating changes by quarter -

Figure IV shows the effect of rating actions on the rating level before and after analyst changes. Based on the same quarterly timeline as shown in Figure III, rating levels in quarters following analyst changes turn out slightly higher (i.e., ratings are lower) compared to quarters before analyst changes. However, the figure points toward a limited magnitude of these differences. Rating levels approximately fluctuate between 8.29 and 8.45.

- Figure IV about here: Rating level by quarter -

B.3. Controls

Financial characteristics of the three CRA subsamples are shown in Table II. These quarterly variables serve as our controls. We control for company size (market capitalization), profitability (EBITDA margin) as well as leverage (net debt to EBITDA ratio and debt to capital ratio) in Section IV. On a cross-sectional basis, the table reveals some differences between the CRAs in the means of variables. This particularly holds for the smallest CRA: companies covered by Fitch tend to be larger compared to both Moody's and S&P with a market capitalization of USD 27.423 billion on average for Fitch and USD 25.070 billion (USD 24.710 billion) for Moody's (S&P). Issuers covered by Fitch are more leveraged (higher debt to capital and net debt to EBITDA ratio) compared to the Moody's and S&P samples. When it comes to profitability measures, all three subsamples show a median of approximately 24% in terms in terms of EBITDA margin. The leverage is less than 45% for all subsamples. Net debt to EBITDA ratio expresses the firms' ability to service their debt. In terms of median, net debt exceeds EBITDA by more than five times. In our regression analysis we control for firm fixed effects in order to take differences between firms into account.

- Table II about here: Financial control variables -

IV. Empirical results

In order to analyze the effects of CRA analyst changes on long-term issuer credit ratings, our empirical strategy is based on estimating fixed effects panel regression models. The dataset allows us to construct a quarterly panel from Q1 2002 until Q4 2015. We focus on two dependent variables, rating changes and rating level.

In parallel to the ratings history for each individual issuer, we add a quarterly timeline of lead analysts covering each firm. Adopting the approach of Jayaratne and Strahan (1996) and Stiroh and Strahan (2003), we aim to measure the changes of CRA analysts as our explanatory variable through a dummy taking the value of 1 if a new CRA analysts is assigned to an issuer in a quarter and 0 if the CRA analyst has not changed. As we observe several CRA analyst changes per issuer over the sample period, such change periods take place repeatedly. This "generalized 'difference-in-difference'" design is also employed by, e.g., Jayaratne and Strahan (1996) (p.639). We can thereby address the difficulty of determining a matching control group for the typical difference-in-difference design, which is not possible using our data, by constructing the control group from the average of all issuers in the sample.

We first investigate the effect of CRA analyst changes on rating changes (see Section IV-A). Our baseline regression specification testing this effect is expressed as follows:

$$\begin{aligned} \textit{Rating change}_{i,t} &= \alpha_i + \alpha_t + \\ &\quad \beta_1 \times \textit{Lead analyst change}_{i,t} + \\ &\quad \beta_n \times X_{i,t} + \varepsilon_{i,t} \end{aligned} \tag{1}$$

Second, we analyze if CRA analyst changes are accompanied by an improvement or deterioration of credit ratings (see Section IV-B). Our baseline regression specification is expressed as follows:

$$\begin{aligned} \textit{Rating}_{i,t} &= \alpha_i + \alpha_t + \\ &\quad \beta_1 \times \textit{Lead analyst change}_{i,t} + \\ &\quad \beta_n \times X_{i,t} + \varepsilon_{i,t} \end{aligned} \tag{2}$$

The dependent variable, Rating $\mathrm{change}_{\mathrm{i,t}}$, is a dummy variable equal to 1 if the credit rating of firm i in quarter t has changed and 0 otherwise. The dependent variable in equation 2, $\text{Rating}_{i,t}$, is the long-term issuer default rating on a numerical scale[15] of firm i in quarter t. α_i and α_t are firm and quarter fixed effects, respectively. Our explanatory variable is Lead analyst $\text{change}_{i,t}$. It is a dummy variable taking the value of 1 if a new CRA analyst is assigned to issuer i in a specific quarter t and 0 if the CRA analyst is not changed. We apply three measures: for the variable "Lead analyst change_1-2 quarters", the dummy is set to 1 for the quarter t when the analyst change occurs and quarter t+1 thereafter. "Lead analyst change_3-4 quarters (5-6 quarters)" is set accordingly for the third and fourth quarter (fifth and sixth quarter) thereafter. Issuer-related control variables for financial fundamentals are summarized in vector $X_{i,t}$. These include the credit rating, leverage/ liquidity (net debt to EBITDA ratio and debt to capital ratio), firm size (market capitalization), and profit (EBITDA margin)[16].

Our approach addresses several empirical challenges. In this context, analyst changes could be endogenously driven by financial fundamentals rather than internal policies. For this reason, we analyze CRA analyst changes occurring simultaneously at all three CRAs. We would expect CRA analysts assigned to an issuer to change at several CRAs at the same time due to the development of this issuer's fundamentals. As shown in Figure V, the ratio of CRA analyst changes simultaneously observed at all three CRAs compared to the overall number of CRA analyst changes per year is low. The figure is constantly below 5% and exhibits a stable pattern over time. Thus, the majority of CRA analyst changes appears to follow distinct patterns specific to the CRA and they are not issuer-related.

- Figure V about here: Simultaneous analyst changes at several CRAs over time -

Another challenge to overcome is a potential omitted variable bias as the credit rating might have changed *in absence* of the CRA analyst changes. Assuming that credit rating processes are fully functional, the most intuitive explanation would be a change in financial fundamentals leading to the rating action. We use firm and quarter fixed effects and several issuer financial fundamentals variables as controls (cf. Sufi (2007)). As a result, both firm-specific time-varying and time-invariant omitted variable concerns should be alleviated.

A. Analyst changes and rating changes

Table III shows the effect of CRA analyst changes on rating changes. Columns 3.1-3.9 report conditional effects including control variables and fixed effects. As for the combined analysis of downgrades and upgrades in columns 3.1-3.3, the likelihood of a rating change is 7.2 p.p. higher in a lead analyst change quarter and the subsequent quarter. This effect is no longer observed for the following quarters. Given the average probability of 5.4%, the economic magnitude of this result is significant. The effect size for our results split by

[15]Cf. Table A-IV in the Appendix presenting the numerical reference scale for the alphanumerical ratings employed. We apply the same standardization of rating scales for all three major CRAs as done by Jewell and Livingston (1999).

[16]In equation 2, the credit rating which is our dependent variable in this analysis. Hence, the credit rating is omitted from the control variables. In unreported analyses, we apply various sets of common financial control variables. Our results are vastly not sensitive to the choice of control variables.

downgrades and upgrades is comparable (columns 3.4 and 3.7)[17]. Apparently, there is no clear direction of the observed rating changes. The economic magnitude of effects persists in columns 3.4 and 3.7. We conclude that analyst changes appear to induce increased rating change activity in the first two quarters of an analyst change. Afterwards, this effect appears to vanish[18].

- Table III about here: Analyst changes and rating changes -

B. Analyst changes and rating level

Columns 4.1-4.3 in Table IV present the regression results conditional on fixed effects and controls for the effect of analyst changes on the rating level. They confirm a positive, statistically significant effect of lead analyst changes on the long-term issuer rating for the total sample entailing all three CRAs in scope. Except for column 4.3, lead analyst changes are associated with a deterioration of the credit rating. On average, ratings are 0.028-0.050 points lower on the 21-point rating scale from 1 (best rating) to 21 (worst rating). This result is limited in terms of economic magnitude, however. Within the balanced increase in rating change activity described in Section IV-A, downgrades and upgrades appear to cancel each other out[19]. We also note that the effects are no longer observed 5-6 quarters after the analyst change. Columns 4.4-4.6 report the unconditional results excluding controls and fixed effects. We only observe statistically significant effects in the first two quarters following the analyst change. Even though the economic magnitude of the effects is higher in column 4.4, the results are qualitatively similar. In comparison, we observe a decrease in magnitude in column 4.1 where we control for financial fundamentals and fixed effects. Despite the statistical significance of these results, we conclude that the effects of analyst changes on the rating level are neither sizable[20], nor do they exhibit a clear-cut direction.

- Table IV about here: Analyst changes and rating level -

[17] Table A-I in the Appendix reports a subsample split by CRA. Overall, we observe similar and consistent effects for all CRAs separately.

[18] Table A-II in the Appendix confirms our results based on a Cox proportional hazard model (following Lugo et al. (2015)). This survival analysis approach also examines the probability of rating changes. Herein, the time to rating action measured in days is the dependent variable. We employ time-varying covariates to model lead analyst changes and control for financial fundamentals. The results are stable across all columns for the three CRAs in scope and constantly at the 1% or 5% level. The lead analyst change coefficients are positive which implies a higher likelihood of rating changes. The lead analyst change coefficient reveal that the hazard of a rating change is higher when an issuer experiences an analyst change. For example, for Moody's, the exponentiated coefficient shows a 43% increase in hazard.

[19] Table A-III in the Appendix reports a subsample split by CRA. Overall, we observe similar effects at Fitch and S&P whereas we do not find significant effects for Moody's. The economic magnitude of the effects remains limited in all subsamples.

[20] A review of the effect of different rating levels on the cost of debt incurred by issuers leads to a similar result. For instance, Baghai et al. (2014) report an increase in bond yield spreads of approximately 0.5 p.p. per rating point decline. This would translate to a cost increase of USD 500,000 for a bond with a principal of USD 100 million in a simplified scenario. Taking the magnitude of our results of 0.028-0.050 rating points into consideration, the cash impact of analyst changes appears limited.

C. Robustness

A potential empirical issue stems from heterogeneous treatment effects given our sample choice focusing on large-cap issuers as well as the sample time frame from 2002-2015. We run a battery of analyses in order to verify whether our results are driven by any of the subsamples described below. We analyze subsamples by firm size to show that our results are not clustered around larger companies. In this analysis, we split the sample into quartiles in terms of market capitalization. Our results are robust in each firm size subsample.

Similar heterogeneity concerns arguably pertain to the investment grade of issuers. For instance, the effect of CRA analyst changes might only apply to sub-investment grade issuers as opposed to more highly rated ones and vice versa. This is especially relevant as one of our dependent variables (rating level) represents the issuers' risk levels. Hence, we are not able control for this factor. We address this question by running an unreported subsample analysis for investment grade issuers and those which are sub-investment grade. We define investment grade issuers as those holding a long-term issuer default rating of better than "BB+" on average. The calculation is based on the numerical scale shown in Table A-IV in the Appendix. Issuers with an average rating worse than "BBB-" are considered sub-investment grade issuers. We conclude that our results of Section IV-A for rating changes are not confined to any of the investment grade subsamples. However, the effects shown in Section IV-B for rating level prevail among investment grade issuers only.

According to prior research, credit ratings (changes) have differential effects on economic outcomes in case of a switch from investment grade to sub-investment grade (Chernenko and Sunderam (2012)) or in case of ratings in proximity to that boundary (Kisgen and Strahan (2010)). This requires us to take a closer look at the boundary segment of our sample. In an untabulated analysis, we extend the regressions for rating changes described by equation 1 by including a different set of outcome variables. First, we include two dummy variables taking the value of 1 if the rating was downgraded (upgraded) from investment grade to sub-investment grade (sub-investment grade to investment grade) in a given quarter or 0 otherwise. Second, two dummy variables taking the value of 1 of the rating was downgraded (upgraded) within the investment or sub-investment grade levels. Our previous results presented in Table III are confirmed.

We also add a subsample analysis for equation 2. One of the subsamples entails sample firms with an average rating within the investment grade to sub-investment grade boundary defined to range from BBB to BB, inclusive. The other subsample includes the remaining firms within an average rating above or below this boundary. The calculation is based on the numerical scale shown in Table A-IV in the Appendix. In the results, the coefficients for lead analyst change_1-2 quarters turn out statistically insignificant in both subsamples. Whereas the lead analyst change_3-4 quarters coefficient remains qualitatively robust. Overall, the coefficients shown in Table IV do not appear to be driven by those firms rated at the boundary between the investment grades.

Moreover, we assert that our results effects are not driven by specific downturn or upturn sub-periods during our sample period from 2002 to 2015. These sub-periods include the years from 2002-2007, 2008-2011, 2008-2015 and 2013-2015, respectively.

V. Conclusion

In this paper, we build upon the existing literature centered on problems of credit ratings and the role of CRA analysts. We extend this literature by focusing on analyst changes and their effect on the probability of rating changes, as well as on the level of long-term issuer ratings. Based on a hand-collected dataset, we are able to track CRA analyst changes of S&P 500 issuers between 2002 and 2015 and link them to the rating history of each individual issuer. We find evidence that the probability of rating actions increases when analysts are newly assigned. We also demonstrate that analyst changes are associated with lower ratings. However, the economic effect in terms of lower ratings is close to negligible and the results apply to investment grade issuers only.

In contrast with the argumentation of CRAs, our results show that rating processes do not achieve their goal of producing consistent rating decisions. Hence, our results provide empirical information for mandatory analyst rotation legislation. On the one hand, our analysis empirically confirms the regulator's notion that credit rating processes at major CRAs were prone to influences from changes in analyst coverage in the past. On the other hand, rating changes subsequent to analyst changes did not exhibit a clear-cut direction. We are also not able to assert that ratings become more conservative to counter ratings inflation.

The main implications of our research appertain to CRAs, policymakers and issuers alike. As for CRAs, our research outcomes call for a careful assessment of internal coverage changes policies. However, the clients of CRAs might not be fond of more frequent analyst changes due to potential benefits from "learning to gaming" (Mählmann (2011), p.475). Another potential reason is the reluctance to explain their business and financial situation to new CRA analysts more frequently. In terms of implications for policy, our results might be informative for regulators in the United States, where CRA analyst-related laws have taken a different path compared to the European Union. Additionally, from the issuer's perspective, a CRA analyst change is actually bad news, as it increases the volatility of the company's rating. Issuers might benefit from taking analyst changes into consideration for the timing of both refinancing efforts and disclosure of information to their CRAs.

The intention of structured credit rating processes by the CRAs aligns with the intention of CRA-related regulation: ensuring impartial credit rating decisions by lowering the likelihood of biases given the astounding amounts of credit volume in the global economy. Our results suggest that the role of organizational processes might have been underestimated as criticism tends to zero in on the CRAs' business models.

References

Altman, E. I. and Rijken, H. A. (2004). How rating agencies achieve rating stability. *Journal of Banking & Finance*, 28(11):2679–2714.

Baghai, R. P., Servaes, H., and Tamayo, A. (2014). Have rating agencies become more conservative? Implications for capital structure and debt pricing. *The Journal of Finance*, 69(5):1961–2005.

Bangia, A., Diebold, F. X., Kronimus, A., Schagen, C., and Schuermann, T. (2002). Ratings migration and the business cycle, with application to credit portfolio stress testing. *Journal of Banking & Finance*, 26(2-3):445–474.

Bank for International Settlements (2019). Global debt securities outstanding by sector. Technical report, Bank for International Settlements.

Bar-Isaac, H. and Shapiro, J. (2011). Credit ratings accuracy and analyst incentives. *The American Economic Review*, 101(3):120–124.

Berg, T., Puri, M., and Rocholl, J. (2013). Loan officer incentives and the limits of hard information. National Bureau of Economic Research working paper no. 19051.

Bolton, P., Freixas, X., and Shapiro, J. (2012). The credit ratings game. *The Journal of Finance*, 67(1):85–111.

Chernenko, S. and Sunderam, A. (2012). The real consequences of market segmentation. *The Review of Financial Studies*, 25(7):2041–2069.

Cole, S., Kanz, M., and Klapper, L. (2015). Incentivizing calculated risk-taking: Evidence from an experiment with commercial bank loan officers. *The Journal of Finance*, 70(2):537–575.

Cornaggia, J., Cornaggia, K. J., and Xia, H. (2016). Revolving doors on Wall Street. *Journal of Financial Economics*, 120(2):400–419.

Croce, A., Lugo, S., and Faff, R. W. (2011). Rating alignment, rating shopping and reputation of credit rating agencies: Evidence from the subprime crisis. Working paper.

Devenow, A. and Welch, I. (1996). Rational herding in financial economics. *European Economic Review*, 40(3):603–615.

Dilly, M. and Mählmann, T. (2016). Is there a boom bias in agency ratings? *Review of Finance*, 20(3):979–1011.

Efing, M. and Hau, H. (2015). Structured debt ratings: Evidence on conflicts of interest. *Journal of Financial Economics*, 116(1):46–60.

E.U. Commission (2009). Credit rating agencies - Regulation (EC) No 1060/2009. Technical report, E.U. Commission.

European Parliament, Council of the European Union (2009). Regulation (EC) No 1060/2009 of the European Parliament and of the Council of 16 September 2009 on Credit Rating Agencies. *Official Journal of the European Union*, 302:1–31.

Fitch Ratings (2016). The ratings process (The ratings process under Fitch criteria). Technical report, Fitch Ratings.

Fitch Ratings (2018). European Union Transparency Report. Technical report, Fitch Ratings.

Fracassi, C., Petry, S., and Tate, G. (2016). Does rating analyst subjectivity affect corporate debt pricing? *Journal of Financial Economics*, 120(3):514–538.

Güttler, A. (2011). Lead-lag relationships and rating convergence among credit rating agencies. *Journal of Credit Risk*, 7(1):95–119.

Güttler, A. and Wahrenburg, M. (2007). The adjustment of credit ratings in advance of defaults. *Journal of Banking & Finance*, 31(3):751–767.

Hertzberg, A., Liberti, J., and Paravisini, D. (2010). Information and incentives inside the firm: Evidence from loan officer rotation. *The Journal of Finance*, 65(3):795–828.

Holmstrom, B. (1982). Moral hazard in teams. *The Bell Journal of Economics*, pages 324–340.

Jaggi, B. and Tang, L. (2015). Geographic location of the firm and credit rating accuracy. *Journal of Accounting, Auditing & Finance*, 32(2):155–181.

Jayaratne, J. and Strahan, P. E. (1996). The finance-growth nexus: Evidence from bank branch deregulation. *The Quarterly Journal of Economics*, 111(3):639–670.

Jewell, J. and Livingston, M. (1999). A comparison of bond ratings from Moody's, S&P and Fitch IBCA. *Financial Markets, Institutions & Instruments*, 8(4):1–45.

Jiang, J., Wang, I. Y., and Wang, K. P. (2018). Revolving rating analysts and ratings of mortgage-backed and asset-backed securities: Evidence from LinkedIn. *Management Science*, 64(12):5832–5854.

Kisgen, D. J., Osborn, M., and Reuter, J. (2016). Analyst promotions within credit rating agencies: Accuracy or bias? National Bureau of Economic Research working paper no. w22477.

Kisgen, D. J. and Strahan, P. E. (2010). Do regulations based on credit ratings affect a firm's cost of capital? *The Review of Financial Studies*, 23(12):4324–4347.

Kliger, D. and Sarig, O. (2000). The information value of bond ratings. *The Journal of Finance*, 55(6):2879–2902.

Liberti, J. M. and Mian, A. R. (2009). Estimating the effect of hierarchies on information use. *The Review of Financial Studies*, 22(10):4057–4090.

Lugo, S., Croce, A., and Faff, R. (2015). Herding behavior and rating convergence among credit rating agencies: Evidence from the subprime crisis. *Review of Finance*, 19(4):1703–1731.

Mählmann, T. (2011). Is there a relationship benefit in credit ratings? *Review of Finance*, 15(3):475–510.

Moody's Investors Service (2017). Ratings process detail. Technical report, Moody's Investors Service.

Qian, J. Q., Strahan, P. E., and Yang, Z. (2015). The impact of incentives and communication costs on information production and use: Evidence from bank lending. *The Journal of Finance*, 70(4):1457–1493.

SEC (2016). Annual report on nationally recognized statistical rating organizations - as required by section 6 of the Credit Rating Agency Reform Act of 2006. Technical report, United States Securities and Exchange Commission.

Skreta, V. and Veldkamp, L. (2009). Ratings shopping and asset complexity: A theory of ratings inflation. *Journal of Monetary Economics*, 56(5):678–695.

Standard & Poor's (2014). Corporate ratings methodology. Technical report, Standard & Poor's.

Standard & Poor's (2017). General description of the credit rating process. Technical report, Standard & Poor's.

Stiroh, K. J. and Strahan, P. E. (2003). Competitive dynamics of deregulation: Evidence from US banking. *Journal of Money, Credit, and Banking*, 35(5):801–828.

Sufi, A. (2007). The real effects of debt certification: Evidence from the introduction of bank loan ratings. *The Review of Financial Studies*, 22(4):1659–1691.

Tables

Table I: Summary statistics - Rating level and rating changes

The table shows shows the number of rating changes per issuer overall (Panel A) and the long-term issuer default rating level mapped on a numerical rating scale shown in Table A-IV in the Appendix (Panel B). For example, "1" equals to "AAA". It also shows the magnitude of rating changes (conditional on change) based on the same numercial long-term issuer default rating scale (Panel C). Panel D shows the number lead analyst changes per issuer. The data encompasses unique credit rating analysts covering S&P 500 issuers between 2002 and 2015. Figures are trimmed at the 1st and 99th percentile.

								Percentiles				
Variable	Subsample	Unit	N (firm-quarter)	Mean	SD	Min	Max	5th	25th	50th	75th	95th
Panel A: Rating actions per issuer												
Downgrades	Fitch	Number	9,817	1.60	1.44	0.00	8.00	0.00	0.00	1.00	2.00	4.00
	Moody's		15,168	1.38	1.38	0.00	9.00	0.00	0.00	1.00	2.00	4.00
	S&P		14,343	1.36	1.45	0.00	9.00	0.00	0.00	1.00	2.00	4.00
Upgrades	Fitch	Number	9,817	1.28	1.28	0.00	6.00	0.00	0.00	1.00	2.00	4.00
	Moody's		15,168	1.35	1.36	0.00	7.00	0.00	0.00	1.00	2.00	4.00
	S&P		14,343	1.40	1.51	0.00	8.00	0.00	0.00	1.00	2.00	4.00
Panel B: Rating level												
Issuer default ratings	Fitch	Class	9,817	8.02	2.45	1.00	19.00	5.00	6.00	8.00	9.00	12.00
	Moody's		15,168	8.54	2.59	1.00	20.00	5.00	7.00	8.00	10.00	13.00
	S&P		14,343	8.17	2.57	1.00	21.00	4.00	6.00	8.00	10.00	13.00
Panel C: Magnitude of rating changes												
Issuer default ratings	Fitch	Class	9,817	1.17	0.45	1.00	4.00	1.00	1.00	1.00	1.00	2.00
	Moody's		15,168	1.21	0.48	1.00	4.00	1.00	1.00	1.00	1.00	2.00
	S&P		14,343	1.17	0.47	1.00	4.00	1.00	1.00	1.00	1.00	2.00
Panel D: Analyst changes per issuer												
Lead analyst	Fitch	Number	9,817	1.77	1.42	0.00	7.00	0.00	1.00	2.00	2.75	4.00
	Moody's		15,168	2.14	1.58	0.00	10.00	0.00	1.00	2.00	3.00	5.00
	S&P		14,343	2.31	1.43	0.00	7.00	0.00	1.00	2.00	3.00	5.00

Table II: Summary statistics - Financial control variables

The table shows summary statistics of issuer financial fundamentals. The sample includes 460 companies of which 317 companies are rated by Fitch, 444 are rated by Moody's and 449 are rated by S&P out of constituents of the S&P 500 (dual class shares have been excluded). Figures are based on cross-sectional quarterly data from 2002 until 2015. Figures are trimmed at the 1st and 99th percentile.

								Percentiles				
Variable	Subsample	Unit	N (firm-quarter)	Mean	SD	Min	Max	5th	25th	50th	75th	95th
Market capitalization	Fitch	USD mm	9,817	27,423	35,708	1,414	232,721	3,573	7,909	14,802	29,630	103,727
	Moody's		15,168	25,070	34,347	1,387	231,789	3,063	6,725	13,084	26,460	97,106
	S&P		14,343	24,710	34,603	1,374	232,721	3,012	6,362	12,632	26,239	96,825
EBITDA margin	Fitch	%	9,817	24.14	15.89	-1.620	83.10	5.19	12.90	20.60	30.70	59.80
	Moody's		15,168	24.60	15.43	-1.620	82.90	6.34	13.50	21.00	31.30	59.50
	S&P		14,343	24.49	15.34	-1.620	82.70	6.10	13.60	21.00	31.20	59.20
Net debt to EBITDA ratio	Fitch	%	9,817	843.40	845.50	-919.40	3,939	-203.00	258.10	644.70	1,255	2,609
	Moody's		15,168	779.60	823.90	-933.70	3,947	-243.60	218.90	597.40	1,159	2,467
	S&P		14,343	764.30	842.10	-927.10	3,947	-271.20	197.60	567.20	1,138	2,520
Debt to capital ratio	Fitch	%	9,817	44.27	20.16	1.95	139.70	16.10	29.00	42.40	56.50	79.40
	Moody's		15,168	42.61	19.85	1.92	139.70	13.60	27.90	40.80	55.10	77.10
	S&P		14,343	42.54	20.42	1.92	139.70	12.60	27.50	40.40	55.40	78.10

Table III: Analyst changes and rating changes

The table shows coefficient estimates and robust standard errors of (fixed effects) panel regression models. The total sample includes firms rated by Fitch, Moody's and S&P. The dependent variable is a dummy variable equal to 1 if the credit rating of an issuer has changed in a given quarter and 0 otherwise. Lead analyst change_1-2 quarters (explanatory variable) is a dummy variable set to 1 for the quarter t when the analyst change occurs and quarter t+1 thereafter. Lead analyst change_3-4 quarters (5-6 quarters) is set accordingly for the third and fourth quarter (fifth and sixth quarter) thereafter. Issuer-related control variables for financial fundamentals include the credit rating, leverage/ liquidity (net debt to EBITDA ratio and debt to capital ratio), firm size (market capitalization), and profit (EBITDA margin). ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Fitch, Moody's and S&P								
	Both actions			Downgrades			Upgrades		
	(3.1)	(3.2)	(3.3)	(3.4)	(3.5)	(3.6)	(3.7)	(3.8)	(3.9)
Lead analyst change_1-2 quarters	0.072***			0.028***			0.042***		
	(0.005)			(0.004)			(0.004)		
Lead analyst change_3-4 quarters		-0.005			-0.001			-0.004	
		(0.004)			(0.003)			(0.003)	
Lead analyst change_5-6 quarters			-0.006*			-0.006***			0.001
			(0.004)			(0.002)			(0.003)
Issuer controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean of dependent variable	0.054	0.054	0.054	0.024	0.024	0.024	0.030	0.030	0.030
Observations	39,328	39,328	39,328	39,328	39,328	39,328	39,328	39,328	39,328
Number of firms	1,068	1,068	1,068	1,068	1,068	1,068	1,068	1,068	1,068
R-squared	0.013	0.005	0.005	0.025	0.022	0.023	0.016	0.011	0.011
Adjusted R-squared	0.012	0.003	0.003	0.024	0.021	0.021	0.014	0.009	0.009

Table IV: Analyst changes and rating level

The table shows coefficient estimates and standard errors of (fixed effects) panel regression models. The total sample includes firms rated by Fitch, Moody's and S&P. The dependent variable is the long-term issuer default rating mapped on a numerical scale (cf. also Table A-IV in the Appendix). Lead analyst change_1-2 quarters (explanatory variable) is a dummy variable set to 1 for the quarter t when the analyst change occurs and quarter t+1 thereafter. Lead analyst change_3-4 quarters (5-6 quarters) is set accordingly for the third and fourth quarter (fifth and sixth quarter) thereafter. Issuer-related control variables for financial fundamentals include leverage/ liquidity (net debt to EBITDA ratio and debt to capital ratio), firm size (market capitalization), and profit (EBITDA margin). ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Fitch, Moody's and S&P					
	(4.1)	(4.2)	(4.3)	(4.4)	(4.5)	(4.6)
Lead analyst change_1-2 quarters	0.028*			0.180***		
	(0.016)			(0.043)		
Lead analyst change_3-4 quarters		0.050***			0.045	
		(0.015)			(0.040)	
Lead analyst change_5-6 quarters			0.013			0.041
			(0.015)			(0.042)
Issuer controls	Yes	Yes	Yes	-	-	-
Firm F.E.	Yes	Yes	Yes	-	-	-
Quarter F.E.	Yes	Yes	Yes	-	-	-
Observations	39,328	39,328	39,328	39,328	39,328	39,328
Number of firms	1,068	1,068	1,068	1,068	1,068	1,068
R-squared	0.096	0.096	0.096	0.000	0.000	0.000
Adjusted R-squared	0.069	0.069	0.069	0.000	0.000	0.000

Figures

Figure I: Rating changes over time

The figure shows the probability of changes (defined as the share of firms experiencing a rating change in a given year) of the long-term issuer rating of S&P 500 issuers rated by Fitch, Moody's and S&P between 2002 and 2015. Downgrades are visualized as dark bars and upgrades are visualized as light gray bars.

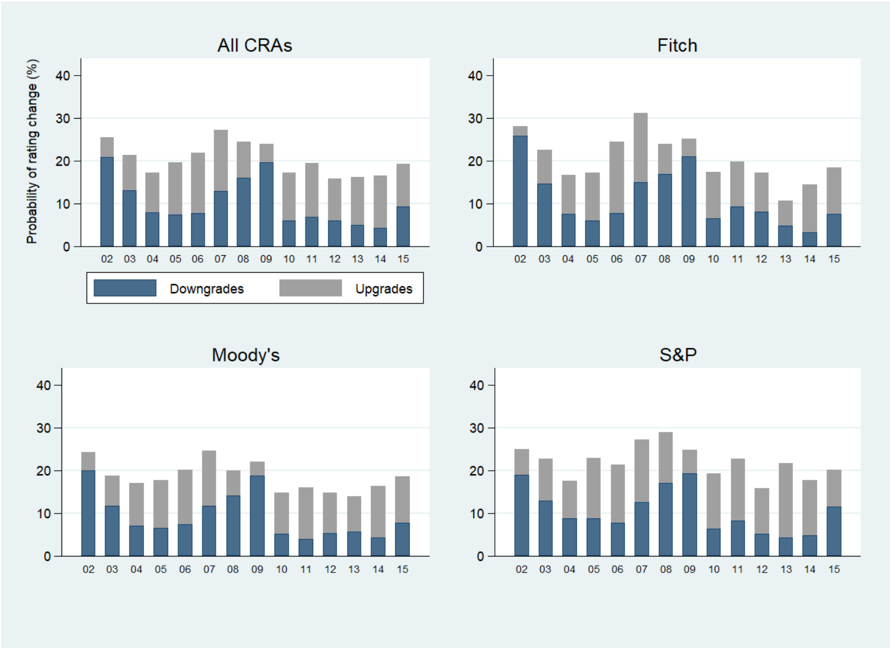


Figure II: Analyst changes over time

The figure shows the probability of lead analyst changes (defined as the share of firms experiencing a lead analyst change in a given year) witnessed by S&P 500 issuers rated by Fitch, Moody's and S&P between 2002 and 2015. Lead analyst changes are visualized as dark bars.

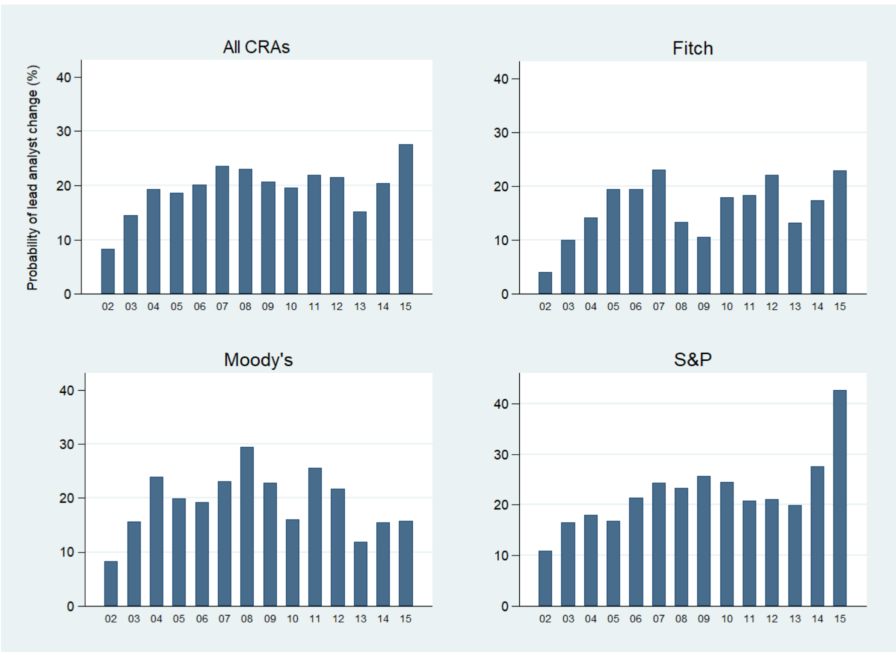


Figure III: Rating changes by quarter

The figure shows the probability of rating changes per quarter (defined as the share of firm-quarters exhibiting a rating change) documented in the quarters before and after a lead analyst change. The share in percent on the y-axis is visualized by dark bars along the quarters in focus. Each point on the x-axis summarizes two quarters.

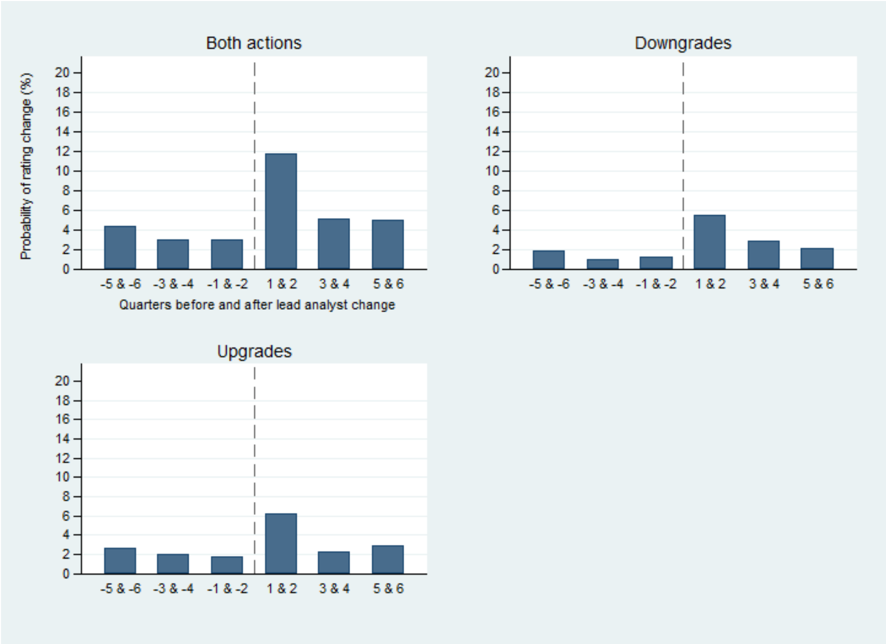


Figure IV: Rating level by quarter

The figure shows the the average long-term issuer rating by Fitch, Moody's and S&P (mapped a on numerical rating scale shown in Table A-IV in the Appendix) documented in the quarters before and after a lead analyst change. The average value on the y-axis is visualized by dark bars along the quarters in focus. Each point on the x-axis summarizes two quarters.

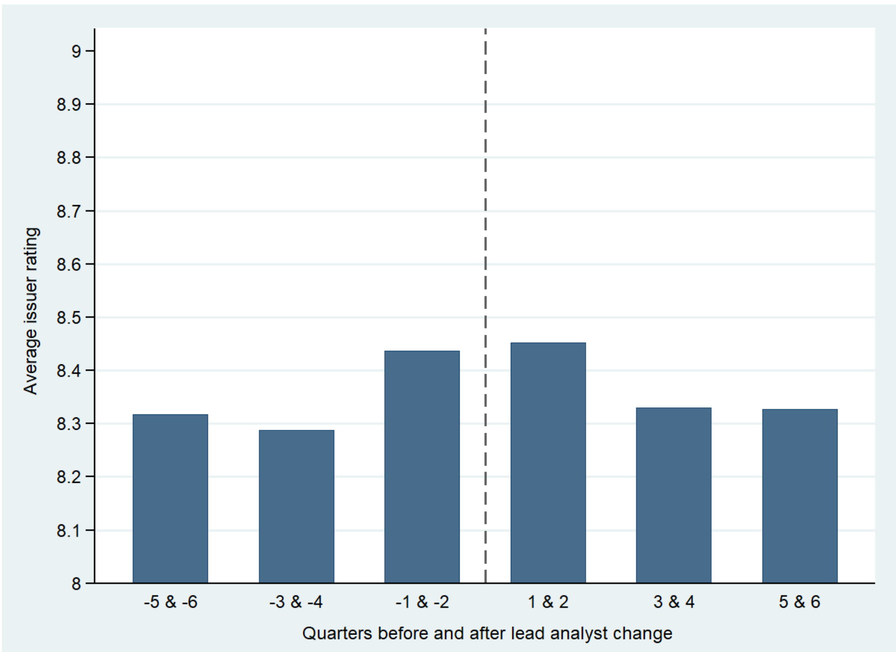
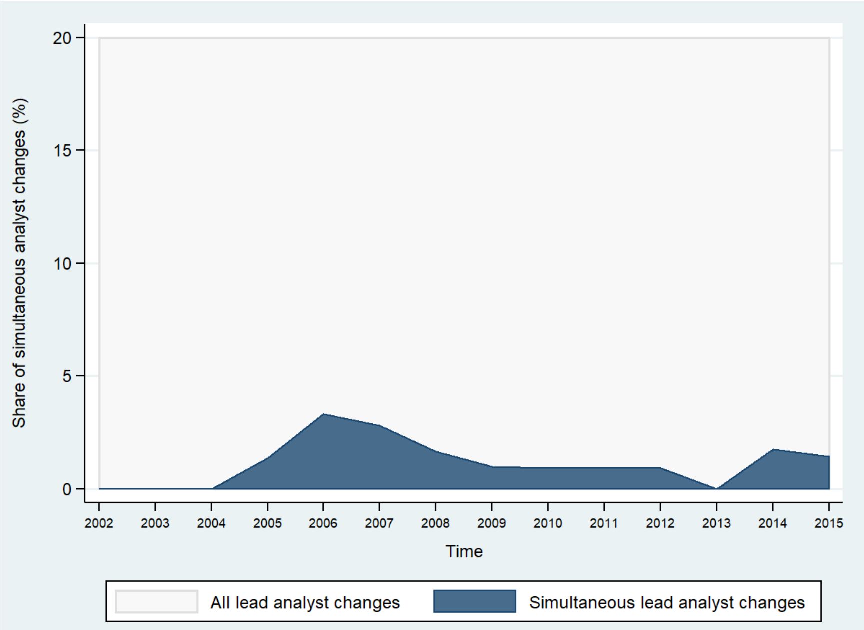


Figure V: Ratio of simultaneous CRA analyst changes at several CRAs over time

The figure shows the ratio of lead analyst changes happening in the same year at Fitch, Moody's and S&P at individual S&P 500 issuers compared to the total number of analyst changes per year between 2002 and 2015. The ratio of simultaneous lead analyst changes is visualized as a dark area.



Appendix

Table A-I: Analyst changes and rating changes - CRA subsamples

The table shows coefficient estimates and robust standard errors of (fixed effects) panel regression models. The analysis includes subsamples of the analysis in Table III by CRA. The dependent variable is a dummy variable equal to 1 if the credit rating of an issuer has changed in a given quarter and 0 otherwise. Lead analyst change_1-2 quarters (explanatory variable) is a dummy variable set to 1 for the quarter t when the analyst change occurs and quarter t+1 thereafter. Lead analyst change_3-4 quarters (5-6 quarters) is set accordingly for the third and fourth quarter (fifth and sixth quarter) thereafter. Issuer-related control variables for financial fundamentals include the credit rating, leverage/ liquidity (net debt to EBITDA ratio and debt to capital ratio), firm size (market capitalization), and profit (EBITDA margin). ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Fitch			Moody's			S&P		
	Both actions								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Lead analyst change_1-2 quarters	0.059***			0.076***			0.079***		
	(0.011)			(0.009)			(0.008)		
Lead analyst change_3-4 quarters		-0.019***			0.001			-0.003	
		(0.007)			(0.006)			(0.006)	
Lead analyst change_5-6 quarters			0.002			-0.018***			-0.004
			(0.008)			(0.006)			(0.006)
Issuer controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean of dependent variable	0.060	0.060	0.060	0.051	0.051	0.051	0.063	0.063	0.063
Observations	9,817	9,817	9,817	15,168	15,168	15,168	14,343	14,343	14,343
Number of firms	269	269	269	400	400	400	399	399	399
R-squared	0.023	0.019	0.018	0.017	0.008	0.008	0.019	0.009	0.009
Adjusted R-squared	0.017	0.013	0.012	0.013	0.004	0.004	0.015	0.005	0.005

Table A-II: Analyst changes and rating changes - Robustness check

The table shows coefficient estimates and standard errors of Cox proportional hazard models for estimating the hazard of rating actions. The sample includes firms rated by Fitch, Moody's and S&P. The dependent variable is the time in days between downgrades and upgrades pertaining to long-term issuer ratings. The time-varying covariate "Lead analyst change" (explanatory variable) takes the value of 1 from the day a new CRA lead analyst appears on a press release or similar publication by a CRA. Until that day, the covariate is assigned a 0 indicating that the CRA analyst covering the respective issuer has not changed yet. Issuer-related control variables for financial fundamentals include leverage/ liquidity (net debt to EBITDA ratio and debt to capital ratio), firm size (market capitalization), and profit (EBITDA margin). ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Fitch	Moody's	S&P
	(1)	(2)	(3)
Lead analyst change	0.516***	0.359***	0.185**
	(0.096)	(0.087)	(0.074)
Issuer controls	Yes	Yes	Yes
Number of firms	269	400	399

Table A-III: Analyst changes and rating level - CRA subsamples

The table shows coefficient estimates and standard errors of (fixed effects) panel regression models. The analysis includes subsamples of the analysis in Table IV by CRA. The dependent variable is the long-term issuer default rating mapped on a numerical scale (cf. also Table A-IV in the Appendix). Lead analyst change_1-2 quarters (explanatory variable) is a dummy variable set to 1 for the quarter t when the analyst change occurs and quarter t+1 thereafter. Lead analyst change_3-4 quarters (5-6 quarters) is set accordingly for the third and fourth quarter (fifth and sixth quarter) thereafter. Issuer-related control variables for financial fundamentals include leverage/ liquidity (net debt to EBITDA ratio and debt to capital ratio), firm size (market capitalization), and profit (EBITDA margin). ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Fitch			Moody's			S&P		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Lead analyst change_1-2 quarters	0.107***			0.034			-0.003		
	(0.034)			(0.028)			(0.024)		
Lead analyst change_3-4 quarters		0.045			0.040			0.063***	
		(0.031)			(0.026)			(0.023)	
Lead analyst change_5-6 quarters			-0.020			0.003			0.042*
			(0.031)			(0.027)			(0.024)
Issuer controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9,817	9,817	9,817	15,168	15,168	15,168	14,343	14,343	14,343
Number of firms	269	269	269	400	400	400	399	399	399
R-squared	0.129	0.128	0.128	0.073	0.073	0.072	0.131	0.132	0.131
Adjusted R-squared	0.099	0.099	0.099	0.044	0.044	0.044	0.069	0.069	0.069

Table A-IV: Numerical reference scale for alphanumerical ratings

The table shows the numerical rating code corresponding to the individual rating agencies' alphanumerical rating scales. The coded ratings are used as the dependent variable for credit rating level.

S&P long-term rating class	Moody's long-term rating class	Fitch long-term rating class	Rating code
AAA	Aaa	AAA	1
AA+	Aa1	AA+	2
AA	Aa2	AA	3
AA-	Aa3	AA-	4
A+	A1	A+	5
A	A2	A	6
A-	A3	A-	7
BBB+	Baa1	BBB+	8
BBB	Baa2	BBB	9
BBB-	Baa3	BBB-	10
BB+	Ba1	BB+	11
BB	Ba2	BB	12
BB-	Ba3	BB-	13
B+	B1	B+	14
B	B2	B	15
B-	B3	B-	16
CCC+	Caa1	CCC+	17
CCC	Caa2	CCC	18
CCC-	Caa3	CCC-	19
CC	Ca	CC	20
C	C	C	21
D		D / DD / DDD	21

Information asymmetry and the pricing of privately placed debt

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Abstract

Based on a dataset including 11,636 private debt placements issued globally between 1999 and 2016, we investigate the association between borrower-lender information asymmetry and the cost of debt for issuers. We observe that information asymmetry due to being a private or unrated firm is associated with higher cost of private debt. Our results equally inform corporate financing decisions and government initiatives aimed at promoting private debt markets in order to expand funding sources for the private sector.

Keywords: *Private placement, cost of debt, information asymmetry, corporate structure*
JEL classification: G30, G32, G38

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I. Introduction

Regulators in the European Union are pursuing plans to promote private debt placements ("PDPs") as an alternative corporate refinancing instrument in addition to bonds and bank loans. The intention is to improve the funding stability in the economy as a whole[1] and to create an alternative private debt market (E.U. Commission (2017, 2015)) for small and medium-sized businesses in particular.

The regulators' efforts were prompted by a profound shift in the debt funding environment symptomatic for the years following the financial crisis of 2008/2009. On the one hand, during the peak quarter of the financial crisis of 2008/2009 alone, new bank loan issuance to large borrowers in the United States tightened by 47%, equal to a three-digit billion USD amount (Ivashina and Scharfstein (2010)). On the other hand, investors have struggled with collapsing fixed income asset returns as a result of quantitative easing policies by central banks (United States Federal Reserve Bank (2017); Korniyenko and Loukoianova (2015)) in response to tightening credit supply. As a consequence, institutional investors such as insurance companies shifted their portfolios "away from gilts towards corporate bonds" (Joyce et al. (2014), p.1).

These developments have caused both borrowers and investors to rediscover PDPs. PDPs are characterized as non-public, unregistered debt securities directly sold to a comparatively small number of sophisticated investors. As opposed to public bonds, PDPs are typically not assessed and monitored by credit rating agencies. Lenders tend to carry out these activities themselves in order to gain transparency regarding the investment (Kwan and Carleton (2010)). PDPs benefit borrowers by supporting diversification away from traditional bank financing channels and by offering lower flotation costs. Potentially, they can be the only financing alternative left for lower investment grade borrowers. For investors, PDPs make it possible to capture risk premia due to the relatively lower public transparency of PDPs and lower borrower investment grade compared to other debt instruments (Denis and Mihov (2003); HIMCO (2013)).

As a result, demand for this type of instrument has risen significantly in recent years with the issuance volume of PDPs amounting to USD 101 billion in 2018 in the United States (Private Placement Monitor (2019); Ernst & Young (2016)), up by 165% compared to 2006 (cf. Figure I). For reference, the issuance of public, corporate debt in total in the United States has only grown by 17% in the same time period of time (SIFMA (2018a))[2].

Empirical research specifically dedicated to PDPs has neither kept up with research on public debt nor the recent upturn of PDPs. Whilst it has been established that PDPs tend to require higher yields compared to public bonds (Kwan and Carleton (2010)), the drivers of the cost of debt within the space of PDPs remain unknown. Prior research on other financing instruments such as loans and bonds (e.g., Saunders and Steffen (2011); Lin et al. (2011)) and agency theory (Jensen and Meckling (1976)) suggest that infor-

[1] "I believe we should complement the new European rules for banks with a Capital Markets Union. To improve the financing of our economy, we should further develop and integrate capital markets. This would cut the cost of raising capital, notably for SMEs, and help reduce our very high dependence on bank funding. [...]", Jean-Claude Juncker, 15th July 2014 (E.U. Commission (2018), p.1)

[2] Compound annual growth rates in this period: 8% for PDPs and 2% for public debt.

mation asymmetry between borrowers and lenders is a driver. Most studies demonstrate that lenders demand a higher risk compensation in case of higher asymmetric information. Moreover, there is existing evidence to show that the cost of debt is determined in conjunction with further borrowing conditions such as collateral and maturity (Dennis et al. (2000)) in loan contracts. The lack of empirical evidence on PDPs might obstruct the design of the above-mentioned policy initiatives as it might prove challenging to target the intended beneficiaries.

We study in this paper whether information asymmetry is associated with higher cost of debt of private placements. The latter constitute a debt market segment characterized by particularly pronounced information asymmetry (Denis and Mihov (2003)) given the limited disclosure requirements. Hence, we would expect information asymmetry also to play an important role for the pricing of debt.

We investigate this issue by, first, evaluating the effect of information asymmetry on the benchmark spread (Berg et al. (2017)) incurred by issuers of PDPs. We define information asymmetry as a) not being publicly listed on a stock exchange, b) not having a credit rating by S&P (Sufi (2007)), c) the asset tangibility[3] (Knyazeva and Knyazeva (2012)) and d) being a subsidiary[4] (Ge et al. (2016)). Second, the association of our measures for information asymmetry and further borrowing conditions determined in conjunction with cost of debt, namely maturity (Berger et al. (2005)) and collateral (Gottesman and Roberts (2007)), are analyzed as an extension. The research focus is on corporate, non-public, non-bank PDPs based on a dataset entailing 11,636 PDPs issued globally between 1999 and 2016. The empirical investigation relies on cross-sectional fixed-effects OLS regression models following Sufi (2007).

Our main findings are as follows: we discover that the costs of private debt are significantly lower for listed, rated and subsidiary firms compared to non-listed, non-rated and non-subsidiary firms. By contrast, firms with higher asset tangibility do not exhibit lower costs of debt. PDPs issued by listed (rated/ subsidiary) issuers incur lower costs of debt of approximately 35 (72/ 67) basis points in comparison to PDPs issued by intransparent firms. The magnitude of listing and rating resembles previous findings on syndicated loans (cf. Saunders and Steffen (2011)). Given the mean of the benchmark spread of 559 basis points, the economic magnitude is also significant. Our results are more pronounced for a subsample of issuers headquartered in the United States. Second, the extension of our analysis reveals that rated firms and asset tangibility ratio exhibit a statistically significant association with maturity. Rated firms' PDPs run one year longer, on average, corresponding to a 10% increase in maturity. The correlation of our proxies for information asymmetry is weaker for collateral. Furthermore, we verify that firm size which is correlated with listing and rating is not the driver of results behind information asymmetry measures. We interpret these findings such that the relatively larger amount of information available to investors about listed and rated firms can be

[3]Defined as the ratio of property, plant and equipment to total assets.

[4]Subsidiary entities could be considered more prone to asymmetric information than to their corporate parents due to the following reasons: first, consolidated accounting might imply that financial information of a subsidiary is subsumed in the parent's financial statements not allowing for entity-level analysis. Second, subsidiaries might be subject to lower disclosure requirements at entity level, e.g., due to smaller firm size.

inferred to be a driver of the investors' risk perception ultimately resulting in a different risk compensation.

The study at hand contributes to the literature on PDPs and to the literature on the role of information asymmetry for debt borrowing conditions. The theoretical model by Diamond (1984) provides a framework for private debt. It can be inferred that the direct lenders of private debt are superior monitors. This is because they perform the role of the intermediary monitor in a consolidated manner by acting as the sole lender and monitor. In contrast, given the number of indirect lenders involved in public debt financing, e.g., free-riding problems might arise if some lenders remain passive. Such problems can only be addressed by consolidating the monitoring tasks on behalf of the different lenders and by paying these tasks (Kwan and Carleton (2010)). The necessity of monitoring capabilities implies a potential role of information asymmetry in the determination of PDP contract terms. Empirical attempts to better understand private debt have identified positive abnormal share price reactions to private placements of convertible debt (Fields and Mais (1991)). Carey (1998) finds lower default rates and magnitude of losses in default of private debt that is sub-investment grade compared to public debt. Analyzing sub-classes of PDPs, Fenn (2000) concludes that there are no long-term differences in yield spreads between 144A and other PDP types. More attention has been paid to private placements of equity[5].

Our study adds a new perspective to the discussion outlined above: We scrutinize the drivers of cost of debt of PDPs in particular. In contrast with the focal point of existing PDP research, our study focuses on borrower-lender information asymmetry as a potential driver of the cost of PDPs. Moreover, we take the perspective of the organizational structure of firms and their subsidiaries, which has not yet been established. So far, PDP literature has treated "the firm" as one homogeneous entity which does not stay abreast of realistic corporate (issuance) structures involving both parent and subsidiary entities.

We further contribute to the broader literature on how information asymmetries and agency issues affect the cost of corporate debt. Many papers relevant to our study base their analysis on theoretical monitoring arguments as introduced by Diamond and Verrecchia (1991). Areas of application range from syndicated loans over banks loans to corporate bonds, concluding for all instruments that information asymmetry is positively correlated with cost of debt. As for syndicated loans, e.g., Saunders and Steffen (2011) and Mattes et al. (2013) find that opaque firms incur higher spreads. Sufi (2007) finds that lenders tend to be geographically closer to borrowers when information asymmetry is severe. Evidence for bank loans is provided by Knyazeva and Knyazeva (2012). They report that, due to increasing information asymmetry and monitoring costs over distance, loan spreads are higher and covenants are more restrictive. As shown by Arena and Dewally (2012), information asymmetry not only matters for loans, however. Investigating a United States sample of corporate bonds, the authors show increasing yield spreads suffered by rural issuers in contrast with urban issuers due to information asymmetries.

[5]Topics covered mainly deal with stock price reactions to announcements of such placements (e.g., Hertzel et al. (2002); Krishnamurthy et al. (2005); Wruck and Wu (2009)). Furthermore, prior research focuses on firm control considerations when privately placing public equity (Cronqvist and Nilsson (2005)) and shareholder coordination (Chakraborty and Gantchev (2013)).

Lu et al. (2010) and Lin et al. (2011) provide evidence for a variety of common measures of information asymmetry, including corporate structure, which influence bond yield spreads in a consistent manner. Ge et al. (2016) employ the existence of offshore subsidiaries as another proxy for information asymmetry driving the cost of debt incurred by issuers.

Apart from information asymmetry, the issuer's bargaining power, agency issues and related control rights have also been found to be associated with debt pricing. According to Davydenko and Strebulaev (2007), higher renegotiation power by issuers leads to higher bond spreads. The existence of options for issuers such as strategic defaults determines bond spreads. In contrast, adding covenants to loan agreements reduces loan yields (Bradley and Roberts (2015)). Feldhütter et al. (2016) discuss the bond pricing implications of creditor control rights. The authors show that creditor control rights are associated with lower bond spreads. The value of reduced borrower-lender asymmetries accompanied by creditor control rights is affirmed by this study, in consequence.

In contribution to earlier research, our study not only extends knowledge to another segment of the debt market, thus improving the overall understanding of determinants of borrowing conditions. But our study also sheds light on a segment of financial markets where information asymmetry between borrowers and investors is higher by definition and should, presumably, be of importance. Finally, our study informs current legislative efforts on PDPs within the European Union's Capital Markets Union initiative (E.U. Commission (2017, 2015)). If mechanisms established for other types of debt apply to PDPs in an analogous manner, then policy measures can systematically be targeted at less transparent firms.

The remainder of this paper is organized as follows: Section II describes the institutional environment of PDPs. Section III presents our data. Empirical results are reported in Section IV. Section V concludes.

II. Institutional environment

PDPs have a long-standing tradition as a means of corporate financing. In the 19th century, railroad and mining companies moved along with settlers pushing the frontier in North America further West and therefore required capital (Boyer et al. (2016)). Most notes issued to investors in those days can be considered private investments since no authority regulating debt issues existed. Successful investments were entirely contingent upon an investor's ability to judge debt offerings (HIMCO (2013)). The regulatory grounds for today's private placements were established in the wake of the financial crisis of 1929/1930 and formalized under Regulation D[6] of the Securities Act of 1933 (SEC (2017)).

Nowadays, according to Private Placement Monitor (2019) as shown in Figure I, the issuance volume of PDPs amounts to USD 101 billion in 2018 in the United States alone following an increase over several years. Indicating the significant role of this instrument, 20% of the American insurance companies' bond portfolios are invested in PDPs in 2015 (NAIC (2017)). PDPs have also gained popularity in European markets and policymakers

[6]Including Rules 504, 505 and 506

attribute major importance to promoting private debt financing instruments as a component of the "Capital Markets Union" regulatory initiative in Europe (E.U. Commission (2015)). The European Commission is currently in the process of designing measures to further develop a European private placements market (cf. E.U. Commission (2017)). Moreover, in 2013, changes to insurance-related laws have enabled French insurance companies to access private debt for their investments. European private placements have experienced a steady increase in volumes ever since (Holmey (2015)).

- Figure I about here: Annual debt issuance over time -

In the context of corporate financing instruments, private placements are possible for debt (i.e., PDP) and equity issues[7]. Focusing on PDPs in this study, these coexist with the portfolio of debt instruments including public bond offerings or loan instruments. In a strict sense, bank loans and syndicated loans in particular can also be considered a form of private debt. Keeping our focus on PDPs with respect to Regulation D of the Securities Act of 1933 as non-bank private debt, we note subsequently that (private) bank debt and non-bank private debt differ in various aspects, e.g., regulation, maturity and placement structure (Denis and Mihov (2003)). Based on figures by Private Placement Monitor (2019) and Ernst & Young (2016), PDPs correspond to 5-8% of the overall issuance volume of corporate bonds in the United States SIFMA (2018b).

PDPs are characterized as non-public, direct sales of non-underwritten debt securities to a comparatively small number of sophisticated investors (SEC (2017); Blackwell and Kidwell (1988)). Typical investors involved in this instrument include specialized institutions such as insurance companies and pension funds (HIMCO (2013); Krishnaswami et al. (1999)) which have the expertise and resources required for a due diligence of the offerings and monitoring at their disposal. PDPs are typically unregistered with regulatory bodies such as the SEC in the United States (Kwan and Carleton (2010)) and issuers are not obliged to publicly disclose any detailed information. There are no public prospectus requirements (SEC (2017)) either. Therefore, investors have to cope with a high degree of information asymmetry.

Due to these characteristics, PDPs differ significantly from publicly offered debt which is subject to a substantially higher degree of monitoring, standardization, filing requirements, lower information asymmetry and usually has a large investor base (Denis and Mihov (2003)). PDPs also differ from bank loans in terms of seniority, maturity, adjustability of interest rates and regulation as argued by Kwan and Carleton (2010). Generally, PDPs feature fixed interest rates as opposed to bank loans and medium to long-term maturities (Carey et al. (1994)). Traditional PDPs tend to be illiquid as well[8]. Consequently, PDPs provide a distinct alternative financing instrument which is less regulated compared to others. Smaller firms with higher credit risk and lower transparency are more likely to issue PDPs (Kwan and Carleton (2010)). Beyond the United States, PDPs

[7]Cf. also private investments in public equity ("PIPE")

[8]This aspect mainly pertains to "traditional" PDPs in the United States as laid down in Regulation D. However, in 1990, the SEC adopted "Rule 144A" for PDPs. PDPs issued according to Rule 144A can be traded among qualified institutional buyers (Fenn (2000)) in order to create a secondary market for these securities. Therefore, Rule 144A PDPs are generally regarded as more liquid than traditional PDPs.

are also known in other jurisdictions. Particularly in Europe, the German "Schuldschein" security exhibits similarities with United States PDPs and even non-German issuers are increasingly relying on it (Whittaker (2015)). European private placements are another similar vehicle gaining acceptance, especially among French issuers and investors (Holmey (2015)).

As far as the process of a PDP issue is concerned, the entire placement process typically takes about 12 weeks from mandate to completion (HIMCO (2013)). The broad process steps (adapted from a detailed account by Carey et al. (1994)) entail a prospecting, a contract term design and a distribution stage followed by a contract writing stage. Many PDPs are placed with the support of a commercial or investment bank purely acting as adviser in structuring, pricing and negotiation. This is in contrast with underwriters in public offerings where banks might be investors as well. Once an issuer has decided to utilize a PDP and selected an adviser, the latter will perform a due diligence of the issuer in order to be able to design the major contract terms. This is the second stage of the process. The two key documents fixing the contract terms are an offer memorandum and a term sheet. Aimed at providing all necessary information to potential investors, these documents include the structure and pricing of the PDP securities. In parallel or subsequent to this stage, the adviser approaches potential investors. Those investors expressing interest in the PDP enter the due diligence stage. In case they are satisfied and once the investment decision has been made in the investor's internal committees, formal letters of commitment are obtained by the adviser. In the final step issuers and their advisers, investors and lawyers arrange the exact contract terms and close the deal. On average, advisers earn a fee equivalent to 6% of the offering for offerings under USD 1 million. The fee monotonically declines to less than 2% for offerings larger than USD 50 million (Ivanov and Bauguess (2013)).

A diversification of capital sources might motivate issuers to choose PDPs (HIMCO (2013)). Apart from a general diversification standpoint, decreased access to bank loan financing resulting from the banks' decreased lending capacity might drive such considerations. Likewise, confidentiality can be better attained by PDPs in case a firm has not issued public debt at the same time. Issuers not willing to disclose business or debt pricing-relevant information to the public or other parties often find the discretion offered by PDPs useful. Furthermore, since documentation, credit rating and registration requirements are comparatively low for PDPs, they offer higher issuing speed and flexibility as well as lower transaction costs and complexity. While PDPs are not exclusively issued by small-sized, lower credit quality firms, their access to public bond markets is potentially restricted resulting from these circumstances. As reported by Denis and Mihov (2003), firms in the lower credit quality ranks tend to borrow from (non-bank) private lenders. With regard to disadvantages of PDPs for issuers, the pool of capital accessible is significantly smaller compared to public bonds. Kwan and Carleton (2010) argue that investors are likely to demand a different risk and illiquidity compensation. Also, covenants tend to be more restrictive and tailored to investors' needs.

From an investor's point of view, on the other hand, the low-yield market environment makes PDP yields comparatively more attractive as these tend to be higher than for public debt (Kwan and Carleton (2010); Denis and Mihov (2003)). This applies to institutional investors which are the dominating lenders of PDP issuers in particular. For institutional investors such as insurance companies which rarely require short-term liquidity, the additional compensation by issuers for the latter is an attractive proposition (NAIC (2017)). At the same time, diversification is considered beneficial by investors, too. The possibility to include customized covenants into PDP contract terms is another advantage valued by many sophisticated investors (HIMCO (2013)). The mode of transaction, based on close communication with the senior management of the issuer, is also a clear difference compared to public markets. In terms of disadvantages for investors, financial risks (cf. credit, liquidity and transparency) as well as financial expert resource requirements to analyze deals should be mentioned.

III. Data

A. Sample construction

Data used in our study stems from Standard & Poor's "Capital IQ", supplemented by data from the International Monetary Fund ((2014)).

Based on Capital IQ's fixed income screening feature, the initial dataset entails PDPs issued globally between the 1977 and 2016. Beyond general security information such as issue type, currency and seniority, the key information available for our analyses is issuer name, benchmark spread[9], offering amount, offering date and maturity date. Currencies are converted into USD using Capital IQ's conversion feature. Further PDP issue-level information such as covenants included (e.g., Bradley and Roberts (2015)) or arrangers involved (e.g., Sufi (2007)) in the transaction has been shown to influence debt pricing in prior literature. Despite the potential relevance, the information about these factors available in our dataset is limited.

Among PDP issuer-related data, the database provides identifiers such as stock tickers, the corporate parent name of the issuer in case the PDP is issued by a subsidiary, the geographic location of both issuer and corporate parent, and industry classifications. We match our PDP issue data with corporate financial statement data, also available from Capital IQ. These variables entail firm size (total assets and revenues), profitability (EBITDA margin), leverage (total debt to assets and interest coverage ratio[10]) and asset tangibility ratio[11] (following Knyazeva and Knyazeva (2012)). We calculate benchmark spreads on our own as the benchmark spread item in the database includes figures for approximately 30% of the PDPs only. Hence, we derive the benchmark spread from the difference between the coupon interest rate of the PDP and the risk-free rate in the year of the PDP offering in the geography of the issuer[12]. Risk-free rates are obtained from Capital IQ as well. For issuers located in Europe, the interest rate of Euro area central

[9]Defined as the spread of interest rate over benchmark.

[10]Defined as the ratio of EBIT to interest expenses.

[11]Defined as the ratio of property, plant and equipment to total assets. It summarizes the degree to which a firm's assets are transparent and tangible.

[12]In an unreported analysis, we determine that our results are robust to the choice of the benchmark spread variable.

government bonds is used. For all other geographies, we utilize the United States treasury interest rate.

Based on the initial sample of PDPs retrieved, we exclude financial firms[13]. Public or sovereign issuers (SIC codes 9121, 9199 and 9311), government bonds or municipal bonds are also removed from the sample. Regarding the sample time frame, PDPs issued between 1999 and 2016 are part of our investigation as these years include a sufficient number of observations for each year. It is the longest history of PDPs in research to date. Following the procedures of related papers, e.g., Lau and Yu (2010), issues from "tax havens" as classified by the International Monetary Fund (2014) are also omitted[14]. Further exclusions are made in case of convertible bonds (cf. Arena and Dewally (2012)) and perpetual bonds.

Further to these exclusions, we apply an aggregation procedure of PDP issues as employed by Arena and Dewally (2012) since our raw sample contains several instances of similar PDPs issues made by the same issuer within a short time frame (see also Denis and Mihov (2003)). We aggregate similar PDPs by the same issuer[15] on a quarterly basis. Specifically, aggregated maturity (cf. Arena and Dewally (2012)), coupon rate and benchmark spreads are calculated as a weighted average of individual issue maturities weighted by the offering amount. We aggregate the latter using the sum of offering amounts.

These steps taken together result in a sample entailing 11,636 non-bank, non-public, corporate PDPs by non-financial issuers between 1999 and 2016. We further restrict this sample to those firms for which all the required financial control variables are available. We arrive at a final sample of 4,652 PDPs included in the analysis[16].

B. Descriptive statistics

Details on characteristics of the PDP issues are reported in Panel A of Table I. On average, USD 449.39 million are offered in a PDP with a maturity of 9.42 years. This is consistent with previously used samples, e.g., Kwan and Carleton (2010), and confirms the medium to long-term nature of PDPs. The average benchmark spread of 559.57 basis points equates to 5.59%. The median equates to 5.45%. Values for spreads are higher in comparison with previous syndicated loan and bond samples (cf. Berg et al. (2017); Arena and Dewally (2012)). This is most likely due to the focus on PDPs which require risk premia in comparison to public bonds. 11% of PDP issues include a collateral. Overall, the data are consistent with typical characteristics of PDPs outlined in Section II. 75% of PDPs in the sample are issued by firms headquartered in the United States. Another 5% of PDPs stem from issuers headquartered in Canada. Europe-based (Asia-based) issuers

[13]In particular, SIC codes 6000-6999 and GICS primary sector codes "Financials" are removed following the approach of the vast majority of fellow scholars, cf. Arena and Dewally (2012); Knyazeva and Knyazeva (2012); Lau and Yu (2010); Sufi (2007); Denis and Mihov (2003).

[14]As far as issuers in the United States are concerned, unreported analyses show that our results are not sensitive to issuers' location in the federal state of Delaware known for its preferential tax treatment.

[15]Criteria for aggregation: if issued by the same issuer with same security type and coupon type and security currency and seniority level.

[16]In an unreported analysis, we show that the PDPs included in the two samples do not exhibit major differences in their characteristics.

account for 8% (5%) of the PDPs.

Regarding characteristics of issuer firms, the majority of firms are rated (59%) and 51% are listed. 38% of firms are subsidiaries whilst hardly any subsidiary is publicly listed. As shown in Panel B of Table I, the average asset tangibility ratio amounts to 39.87% with the median being in the same order of magnitude. Leverage expressed as debt-to-capital ratio is 42.41% and similar in terms of median. All sample firms exhibit positive operational profitability expressed as EBITDA margin ranging from 0.82% to 80.90% at an average of 22.92% which is similar for the median. In line with the majority of PDPs placed by corporate parent entities, the majority of firms show similar levels of revenue as their parent entity with an average of 90.59% for the issuer role variable. As for EBIT to interest expense (interest coverage ratio), the average amounts to 6.37x. The median as well as the 75th percentile are lower.

- Table I about here: Summary statistics -

Our initial graphical analysis shown in Figure II compares the average benchmark spread of PDPs incurred by issuers. The results point toward the importance of having a rating. PDPs by rated firms exhibit the lowest average spreads among the four categories. It amounts to 515 basis points as compared to 676 basis points for listed and unrated firms. Whereas PDPs issued by listed firms do not appear to have significantly lower spreads as compared to non-listed firms. Only for listed firms which are rated at the same time, spreads are 7% lower in comparison to rated, yet non-listed firms. In fact, being listed without a credit rating appears to be linked to the highest cost of debt. Spreads incurred by firms in this category are even higher in contrast with firms which are neither listed nor rated. Overall, the graphical analysis provides preliminary evidence of a positive association of information asymmetry and benchmark spreads. This result also represents motivation for subsequent multivariate analyses.

- Figure II about here: Benchmark spread by listing/ rating status -

As another proxy for information asymmetry, Figure III presents the analysis of benchmark spreads incurred by subsidiary entities (belonging to a corporate parent) versus corporate parent entities (owning subsidiaries) in the context of listing status. We observe that listed subsidiaries exhibit the lowest average benchmark spread of 521 basis points. The second-lowest spread is found for listed corporate parents incurring 2% lower spreads. Regardless of entity type, listed issuers have lower benchmark spreads than non-listed ones. Overall, subsidiaries have lower average spreads than parent entities.

- Figure III about here: Benchmark spread by entity type and listing/ rating status -

IV. Empirical results

For our empirical analysis, we follow the study by Sufi (2007). We employ cross-sectional fixed effects OLS regression models. The subjects of analysis are non-bank, non-public, corporate PDPs issued globally by non-financial issuers between 1999 and 2016. The dependent variable of the primary regression models is benchmark spread as derived in Section III-A. It is defined as the spread of PDP interest rate over benchmark (following, e.g., Saunders and Steffen (2011); Arena and Dewally (2012)). The explanatory variables are commonly utilized proxies for information asymmetry: a) listed firm (being publicly listed on a stock exchange) b) rated firm (having a credit rating by S&P, following, e.g., Sufi (2007)), c) asset tangibility ratio (following, e.g., Knyazeva and Knyazeva (2012)) and d) subsidiary (being a subsidiary versus of a corporate parent entity, following, e.g., Ge et al. (2016)).

We address several identification challenges in our approach. First, these stem from potential unobserved heterogeneity of issuer firms beyond information asymmetry. The financial control variables and year, industry and country fixed effects controlling for issuer and PDP-related factors help us intercepting this issue. In addition, we perform subsample analyses to test our findings for robustness.

Second, there exists a potential correlation of our explanatory variable, information asymmetry, and firm size as revealed by a descriptive analysis in Figure IV. Panel A indicates that benchmark spreads might rather be a function of firm size than information asymmetry. This is confirmed by Panel B showing that issuers which are both listed and rated tend to be larger firms. The issue is reinforced by Panel D for entity type and listing. Therefore, Panel C takes a closer look at the distribution of asset tangibility ratios by listing and rating status. Herein, asset tangibility appears to be orthogonal to firm size. Consequently, we not only control for firm size in our regressions but we also include asset tangibility as one measure of information asymmetry.

- Figure IV about here: Relation of listing/ rating status with benchmark spread, firm size and asset tangibility -

Third, endogeneity is a concern grounded on two reasons: both the discretion exercised by the issuers' management influencing our control variables shortly prior to issuing a PDP as well as potential reverse causality. Since our dataset includes a time series of issuer firm controls, we are able partially rule out these concerns by lagging our control variables by one year. Apart from this, investors considering a PDP investment are likely to overweight past performance in their judgment in contrast with current performance in the year of offering.

A. Information asymmetry and benchmark spread

The first part of the empirical analyses investigates the cost of debt implications of information asymmetry. Based on the discussion in Section I, a positive relationship can be expected. The baseline specification employed to test this association can be expressed as follows:

$$
\begin{aligned}
Benchmark\ spread_{p,i,y,c,s} \quad = \quad & \alpha_y + \alpha_c + \alpha_s + \\
& \beta_1 \times Listed\ firm_{i,y,c,s} + \beta_2 \times Rated\ firm_{i,y,c,s} + \\
& \beta_3 \times Asset\ tangibility_{i,y,c,s} + \beta_4 \times Subsidiary_{i,y,c,s} + \\
& \beta_n \times X_{p,i,y,c,s} + \beta_n \times Y_{i,y,c,s,t-1} + \varepsilon_{p,i,y,c,s}
\end{aligned} \tag{1}
$$

The dependent variable, benchmark $\text{spread}_{\text{p,i,y,c,s}}$, of each PDP issue p of issuer i in country c in (industrial) sector s issued in year y is measured in basis points. α_y, α_c and α_s are year, country and sector fixed effects, respectively. The year refers to the year of issuance, country denotes where the issuer firm is headquartered and sector is the primary industry of the issuer firm according to GICS classification. Our main explanatory variable is captured by four proxies as defined above: listed firm (β_1), rated firm (β_2), asset tangibility ratio (β_3) and subsidiary (β_4). Furthermore, we include a set of control variables on both the PDP issue as well as the issuer level in order to consider financial fundamentals-related effects. PDP issue controls are summarized in vector X while vector Y refers to issuer firm control variables lagged to the fiscal year prior to placement. PDP issue control variables used are maturity measured in years, offering amount in USD millions, seniority level coded from junior to more senior levels and collateral which is a dummy variable taking the value of 1 if the issue is secured and 0 otherwise. Issuer firm controls cover size (revenues), profitability (EBITDA margin), leverage (debt to capital ratio). Further, issuer role (e.g., sales-focused entity versus production entity) defined as the ratio of an entity's revenues to its corporate parent revenues measured in percent and financial stability (interest coverage ratio) are included.

Table II presents the results of equation 1 with four different sets of the above-mentioned fixed effects included. First of all, we observe a statistically significant effect of listed firm, rated firm and subsidiary and no effect of asset tangibility ratio. The strongest effect is for rated firms as these exhibit >70 basis points lower benchmark spreads on average. The effect of listed firm is economically weaker but stable showing approximately 30 basis points lower spreads. All effects are also economically significant in comparison to the mean of the dependent variable of 559.57 basis points. In addition, findings from prior literature are confirmed except for the negative coefficient estimate for subsidiaries.

For the subsidiary coefficient, we are cognizant that one would expect a comparable magnitude of approximately 60 basis points but the opposite sign based on, e.g., Ge et al. (2016). We attribute the result to the fact that for 95% (85%) of the PDPs that are issued by subsidiaries, the subsidiary belongs to a listed (rated) corporate parent entity. The coefficient for subsidiaries only remains negative and significant for subsidiaries of transparent[17] parent entities, as we determine in an unreported analysis. This confirms the previously observed effects of transparency indicators. Regardless of the set of fixed effects applied, the coefficient estimates remain stable in terms of statistical significance and economic magnitude. In conclusion, transparent firms exhibit lower spreads. Information

[17] We follow Sufi (2007) in defining firms that are publicly listed and rated at the same time as transparent firms.

asymmetry is associated with higher spreads which is in line with findings on syndicated loans by Saunders and Steffen (2011) and Mattes et al. (2013).

- *Table II about here: Information asymmetry and benchmark spread (full sample)* -

Since the United States are the largest and most developed market for PDPs within our global sample, we perform a robustness check regarding the issuers' origins. We therefore split the sample into those PDPs issued by firms headquartered in the United States (75% of PDPs in the sample) and those headquartered elsewhere in the world. Equation 1 and all variables as well as fixed effects therein remain unaltered[18].

Table III reports the results for the United States subsample (column 3.1) and the rest of the world (column 3.2). Overall, our results appear more pronounced for United States issuers as column 3.1 shows mostly stronger coefficient estimates in terms of magnitude compared to the full sample results in Table II. Also, the effect of asset tangibility ratio turns out statistically (though not economically) significant. On the other hand, for non-United States issuers, the negative coefficient of rated firm remains which is not the case for the remaining explanatory variables. Hence, we observe weaker effects for this subsample.

- *Table III about here: Information asymmetry and benchmark spread (subsamples)* -

B. Information asymmetry, maturity and collateral

In order to further scrutinize the effect of information asymmetry on borrowing conditions, we extend the analysis above by two further components of debt contracts: maturity and collateral (cf. Dennis et al. (2000))). With regard to the empirical set-up, we utilize equation 1 replacing the dependent variable(s) accordingly. In the case of maturity of PDP issue p of issuer i in country c in (industrial) sector s issued in year y measured in years (collateral measured as a binary variable taking the value of 1 if the issue is secured and 0 otherwise) being used, maturity (collateral) are not part of the set of control variables. All other variables are identical.

Table IV presents the results for maturity (collateral) as the dependent variable in columns 4.1-4.4 (4.5-4.8). Rated firm and asset tangibility ratio exhibit a statistically significant association with maturity. Rated firms' PDPs run one year longer, on average which corresponds to approximately 10% of the mean of the dependent variable. The economic significance of asset tangibility ratio is limited, however. For listed firms, the PDP maturity is 0.7-0.9 years shorter, on average. Our results are not affected by the choice of fixed effects.

As far as results for collateral are concerned, statistical significance is observed only for the rated firm coefficient. Its estimate of 3.8% in column 4.8 suggests a narrow magnitude relative to the fact that almost 90% of PDPs in the sample include no collateral. Yet, we can ascribe economic significance in relation to the mean of the dependent variable. Nevertheless, information asymmetry measures are broadly not correlated with collateral.

[18]Country fixed effects are not included in the United States-only subsample.

This result needs to be seen in the institutional context of PDPs rarely entailing a collateral which is reflected in our sample. In summary, despite some of the proxies exhibiting significant effects, information asymmetry does not explain maturity and collateral in PDP agreements to the same extent as compared to benchmark spreads.

- Table IV about here: Information asymmetry, maturity and collateral -

V. Conclusion

In this paper, we advance the existing literature on the role of information asymmetry in the context of financing costs. For the first time, we offer a perspective on the information asymmetry factors driving the cost of (non-bank) private debt.

Our cross-sectional fixed-effects regression analysis is based on one of the most comprehensive datasets to date on PDPs issued globally between 1999 and 2016. It allows us to ascertain that there is a significant and negative association between being listed, rated, a subsidiary and the cost of private debt conditional on a range of financial characteristics. These effects apply for United States-based issuers more strongly. We confirm phenomena observed in prior literature for other types of debt, e.g., syndicated loans. Information asymmetry results in a higher compensation for risk. As an extension of the analysis to encompass other PDP contract terms, namely maturity and collateral, we show that only maturity is associated with information asymmetry. Overall, results are less pronounced compared to those for cost of debt.

As PDPs are gaining momentum, our study closes the gap regarding the understanding of the role of information asymmetry for borrowing conditions. We add to the PDP literature and extend literature concerning the effect of information asymmetry on other types of debt. Moreover, our findings might foster the currently ongoing policy development process in the European Union targeted at expanding PDP markets as an additional, alternative means of corporate funding (E.U. Commission (2015, 2017)). Measures enhancing the transparency of firms apart from laborious steps such as seeking a public listing appear worth considering based on our results. Examples include adjusted legal frameworks or platforms for information disclosure. This applies in particular to firms unaccustomed to the aforementioned instrument. Hence, smaller, private firms such as SMEs could be targeted with regulatory support. For seekers and providers of capital alike, there is a risk of a new credit crunch (Isaac (2019)) and continued quantitative easing by central banks (European Central Bank (2019)), respectively. This necessitates that the new policy measures rely on a data-driven design process in order to be most effective. Further implications of our study for capital-seeking firms point toward an increased likelihood that information asymmetry-reducing measures might pay off.

References

Arena, M. P. and Dewally, M. (2012). Firm location and corporate debt. *Journal of Banking & Finance*, 36(4):1079–1092.

Berg, T., Saunders, A., Steffen, S., and Streitz, D. (2017). Mind the gap: The difference between US and European loan rates. *The Review of Financial Studies*, 30(3):948–987.

Berger, A. N., Espinosa-Vega, M. A., Frame, W. S., and Miller, N. H. (2005). Debt maturity, risk, and asymmetric information. *The Journal of Finance*, 60(6):2895–2923.

Blackwell, D. W. and Kidwell, D. S. (1988). An investigation of cost differences between public sales and private placements of debt. *Journal of Financial Economics*, 22(2):253–278.

Boyer, P. S., Clark, C. E., Halttunen, K., Kett, J. F., and Salisbury, N. (2016). *The enduring vision: A history of the American people*. Cengage Learning.

Bradley, M. and Roberts, M. R. (2015). The structure and pricing of corporate debt covenants. *The Quarterly Journal of Finance*, 5(02):1550001.

Carey, M. (1998). Credit risk in private debt portfolios. *The Journal of Finance*, 53(4):1363–1387.

Carey, M., Prowse, S., Rea, J., and Udell, G. (1994). The economics of the private placement market. *United States Federal Reserve System Bulletin*, 80:1–111.

Chakraborty, I. and Gantchev, N. (2013). Does shareholder coordination matter? Evidence from private placements. *Journal of Financial Economics*, 108(1):213–230.

Cronqvist, H. and Nilsson, M. (2005). The choice between rights offerings and private equity placements. *Journal of Financial Economics*, 78(2):375–407.

Davydenko, S. A. and Strebulaev, I. A. (2007). Strategic actions and credit spreads: An empirical investigation. *The Journal of Finance*, 62(6):2633–2671.

Denis, D. J. and Mihov, V. T. (2003). The choice among bank debt, non-bank private debt, and public debt: evidence from new corporate borrowings. *Journal of Financial Economics*, 70(1):3–28.

Dennis, S., Nandy, D., and Sharpe, I. G. (2000). The determinants of contract terms in bank revolving credit agreements. *Journal of Financial and Quantitative Analysis*, pages 87–110.

Diamond, D. W. (1984). Financial intermediation and delegated monitoring. *The Review of Economic Studies*, 51(3):393–414.

Diamond, D. W. and Verrecchia, R. E. (1991). Disclosure, liquidity, and the cost of capital. *The Journal of Finance*, 46(4):1325–1359.

Ernst & Young (2016). EY US private placement market investor survey 2016. Technical report, Ernst & Young.

E.U. Commission (2015). Green paper: Building a capital markets union. Technical report, E.U. Commission.

E.U. Commission (2017). Identifying market and regulatory obstacles to the development of private placement of debt in the EU. Technical report, E.U. Commission.

E.U. Commission (2018). Deepening Europe's economic and monetary union - Update ahead of the Euro Summit of December 2018. Technical report, E.U. Commission.

European Central Bank (2019). Press release: Monetary policy decisions, 24th of October 2019. Technical report, European Central Bank.

Feldhütter, P., Hotchkiss, E., and Karakaş, O. (2016). The value of creditor control in corporate bonds. *Journal of Financial Economics*, 121(1):1–27.

Fenn, G. W. (2000). Speed of issuance and the adequacy of disclosure in the 144A high-yield debt market. *Journal of Financial Economics*, 56(3):383–405.

Fields, L. P. and Mais, E. L. (1991). The valuation effects of private placements of convertible debt. *The Journal of Finance*, 46(5):1925–1932.

Ge, W., Kim, J.-B., Li, T., and Li, Y. (2016). Offshore operations and bank loan contracting: Evidence from firms that set up subsidiaries in offshore financial centers. *Journal of Corporate Finance*, 37:335–355.

Gottesman, A. A. and Roberts, G. S. (2007). Loan rates and collateral. *Financial Review*, 42(3):401–427.

Hertzel, M., Lemmon, M., Linck, J. S., and Rees, L. (2002). Long-run performance following private placements of equity. *The Journal of Finance*, 57(6):2595–2617.

HIMCO (2013). Strategy insights: private placement debt. Technical report, HIMCO.

Holmey, O. (2015). Young Euro PP's three tests: new countries, QE and defaults. In *Global Capital - Private debt markets*. Euromoney Institutional Investor.

International Monetary Fund (2014). Offshore financial centers (OFCs): IMF staff assessments. Technical report, International Monetary Fund.

Isaac, A. (2019). Weakened European banks vulnerable to another credit crunch. *The Telegraph*.

Ivanov, V. and Bauguess, S. (2013). Capital raising in the US: An analysis of unregistered offerings using the Regulation D exemption, 2009-2012. *United States Securities and Exchange Commission White Paper*, pages 1–22.

Ivashina, V. and Scharfstein, D. (2010). Bank lending during the financial crisis of 2008. *Journal of Financial Economics*, 97(3):319–338.

Jensen, M. C. and Meckling, W. H. (1976). Theory of the firm: Managerial behavior, agency costs and ownership structure. *Journal of Financial Economics*, 3(4):305–360.

Joyce, M., Liu, Z., and Tonks, I. (2014). Institutional investor portfolio allocation, quantitative easing and the global financial crisis. Bank of England working paper no. 510.

Knyazeva, A. and Knyazeva, D. (2012). Does being your bank's neighbor matter? *Journal of Banking & Finance*, 36(4):1194–1209.

Korniyenko, Y. and Loukoianova, E. (2015). The impact of unconventional monetary policy measures by the systemic four on global liquidity and monetary conditions. International Monetary Fund working paper no. 15/287.

Krishnamurthy, S., Spindt, P., Subramaniam, V., and Woidtke, T. (2005). Does investor identity matter in equity issues? Evidence from private placements. *Journal of Financial Intermediation*, 14(2):210–238.

Krishnaswami, S., Spindt, P. A., and Subramaniam, V. (1999). Information asymmetry, monitoring, and the placement structure of corporate debt. *Journal of Financial Economics*, 51(3):407–434.

Kwan, S. H. and Carleton, W. T. (2010). Financial contracting and the choice between private placement and publicly offered bonds. *Journal of Money, Credit and Banking*, 42(5):907–929.

Lau, S. T. and Yu, J. (2010). Does proximity matter in international bond underwriting? *Journal of Banking & Finance*, 34(9):2027–2041.

Lin, C., Ma, Y., Malatesta, P., and Xuan, Y. (2011). Ownership structure and the cost of corporate borrowing. *Journal of Financial Economics*, 100(1):1–23.

Lu, C.-W., Chen, T.-K., and Liao, H.-H. (2010). Information uncertainty, information asymmetry and corporate bond yield spreads. *Journal of Banking & Finance*, 34(9):2265–2279.

Mattes, J. A., Steffen, S., and Wahrenburg, M. (2013). Do information rents in loan spreads persist over the business cycles? *Journal of Financial Services Research*, 43(2):175–195.

NAIC (2017). Private placements. Technical report, National Association of Insurance Commissioners.

Private Placement Monitor (2019). 2019 H1 USPP League Table analysis. Technical report, Private Placement Monitor - PPM DataField.

Saunders, A. and Steffen, S. (2011). The costs of being private: Evidence from the loan market. *The Review of Financial Studies*, 24(12):4091–4122.

SEC (2017). Regulation D. Technical report, United States Securities and Exchange Commission.

SIFMA (2018a). SIFMA Fact Book 2018. Technical report, Securities Industry and Financial Markets Association.

SIFMA (2018b). United States corporate bond issuance. Technical report, Securities Industry and Financial Markets Association.

Sufi, A. (2007). Information asymmetry and financing arrangements: Evidence from syndicated loans. *The Journal of Finance*, 62(2):629–668.

United States Federal Reserve Bank (2017). Recent balance sheet trends - Total assets of the Federal Reserve. Technical report, Board of Governors of the Federal Reserve System.

Whittaker, E. (2015). Schuldschein: will fame make or break its unique strengths? In *Global Capital - Private debt markets*. Euromoney Institutional Investor.

Wruck, K. H. and Wu, Y. (2009). Relationships, corporate governance, and performance: Evidence from private placements of common stock. *Journal of Corporate Finance*, 15(1):30–47.

Tables

Table I: Summary statistics

The table shows summary statistics of PDP issues (Panel A) and issuer firms (Panel B) of a sample entailing 4,652 non-bank, non-public, corporate PDPs by 1,691 non-financial issuers between 1999 and 2016 globally. PDPs by the same issuer with similar characteristics are aggregated on a quarterly basis. In this case, aggregated values for maturity and benchmark spreads are included and are calculated as a weighted average of individual issue characteristics weighted by the offering amount. Offering amounts are aggregated using their sum. Benchmark spread is defined as the spread of interest rate over benchmark. Collateral is is a dummy variable taking the value of 1 if the issue is secured and 0 otherwise. For issuer firm-specific characteristics, values lagged by one fiscal year before the issuance are presented. Asset tangibility is defined as the ratio of property, plant and equipment to total assets. Leverage is defined as the ratio of debt to capital. The EBIT to interest expense ratio refers to the interest coverage ratio. Issuer role (e.g., sales-focused entity versus production entity) is defined as the ratio of an entity's revenues to its corporate parent revenues measured in percent. Figures are trimmed at the 1st and 99th percentile.

							Percentiles				
	Unit	N	Mean	SD	Min	Max	5th	25th	50th	75th	95th
Panel A: PDP issue characteristics											
Benchmark spread	Bps	4.652	559.57	251.45	40.46	1,270.52	165.00	376.57	545.26	730.00	1,002.50
Maturity	Years	4.652	9.42	5.86	1.02	32.12	4.58	6.76	8.06	10.03	30.02
Collateral included	Binary	4.652	0.11	0.31	0.00	1.00	0.00	0.00	0.00	0.00	1.00
Offering amount	USD mm	4.652	449.38	379.65	0.13	2,500.00	65.00	200.00	350.00	551.55	1,200.00
Panel B: issuer firm characteristics											
Asset tangibility ratio	%	4.652	39.87	26.19	0.37	92.96	3.92	16.37	37.97	60.94	85.11
Leverage	%	4.652	42.41	22.69	0.62	149.02	11.82	26.73	38.55	53.99	83.84
EBIT to interest expense	X	4.652	6.37	11.28	0.10	119.80	0.50	1.50	2.99	6.08	23.40
Revenues	USD mm	4.652	7,491.03	15,372.13	11.80	119,493.00	208.00	783.40	2,240.60	7,177.10	31,202.10
Issuer role	%	4.652	90.59	52.56	0.56	683.72	7.95	100	100	100	102.85
EBITDA margin	%	4.652	22.92	15.62	0.82	80.90	4.86	11.60	19.10	30.30	56.20

Table II: Information asymmetry and benchmark spread

The table shows coefficient estimates and standard errors of fixed-effects OLS regression models. The sample for all columns includes 4,652 non-bank, non-public, corporate PDPs by 1,691 non-financial issuers between 1999 and 2016 globally. The dependent variable is the benchmark spread measured in basis points. It is defined as the spread of interest rate over benchmark. Listed firm is a dummy variable equal to 1 if the issuer is publicly listed on a stock exchange and 0 otherwise. Rated firm is a dummy variable taking the value if 1 if the firm has a credit rating by S&P and 0 otherwise. Asset tangibility ratio is the ratio of property, plant and equipment to total assets measured in percent. Subsidiary is a dummy variable taking the value of 1 if the issuer is not the same legal entity as the corporate parent and 0 otherwise. PDP issue controls include: maturity measured in years, offering amount in USD millions, seniority level coded from junior to more senior levels and collateral which is a dummy variable taking the value of 1 if the issue is secured and 0 otherwise. Issuer controls refer to a set of lagged financial control variables at the issuer level including revenues in USD millions, EBITDA margin in percent, leverage (debt to capital ratio) in percent, issuer role (e.g., sales-focused entity versus production entity) defined as the ratio of an entity's revenues to its corporate parent revenues measured in percent as well as EBIT to interest expense in multiples. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Full sample			
	(2.1)	(2.2)	(2.3)	(2.4)
Listed firm	-22.918**	-33.113***	-33.839***	-35.350***
	(10.510)	(8.625)	(8.427)	(8.548)
Rated firm	-75.460***	-85.349***	-71.784***	-71.924***
	(8.221)	(6.802)	(6.679)	(6.668)
Asset tangibility ratio	-0.077	-0.104	-0.255*	-0.190
	(0.141)	(0.116)	(0.134)	(0.134)
Subsidiary	-73.007***	-71.448***	-57.136***	-66.842***
	(10.477)	(8.614)	(8.503)	(8.597)
Issuer controls	Yes	Yes	Yes	Yes
PDP issue controls	Yes	Yes	Yes	Yes
Year F.E.	-	Yes	Yes	Yes
Industry F.E.	-	-	Yes	Yes
Country F.E.	-	-	-	Yes
Mean of dependent variable	559.57	559.57	559.57	559.57
Observations	4,652	4,652	4,652	4,652
R-squared	0.221	0.481	0.513	0.546
Adjusted R-squared	0.219	0.477	0.509	0.536

Table III: Information asymmetry and benchmark spread - Subsamples

The table shows coefficient estimates and standard errors of fixed-effects OLS regression models. The sample in column 3.1 includes 3,492 non-bank, non-public, corporate, PDPs by 1,231 non-financial issuers headquartered in the United States between 1999 and 2016. The sample in column 3.2 includes 1,160 non-bank, non-public, corporate, private PDPs by 460 non-financial issuers headquartered outside of the United States between 1999 and 2016. The dependent variable is the benchmark spread measured in basis points. It is defined as the spread of interest rate over benchmark. Listed firm is a dummy variable equal to 1 if the issuer is publicly listed on a stock exchange and 0 otherwise. Rated firm is a dummy variable taking the value of 1 if the firm has a credit rating by S&P and 0 otherwise. Asset tangibility ratio is the ratio of property, plant and equipment to total assets measured in percent. Subsidiary is a dummy variable taking the value of 1 if the issuer is not the same legal entity as the corporate parent and 0 otherwise. PDP issue controls include: maturity measured in years, offering amount in USD millions, seniority level coded from junior to more senior levels and collateral which is a dummy variable taking the value of 1 if the issue is secured and 0 otherwise. Issuer controls refer to a set of lagged financial control variables at the issuer level including revenues in USD millions, EBITDA margin in percent, leverage (debt to capital ratio) in percent, issuer role (e.g., sales-focused entity versus production entity) defined as the ratio of an entity's revenues to its corporate parent revenues measured in percent as well as EBIT to interest expense in multiples. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	U.S. subsample	Non-U.S. subsample
	(3.1)	(3.2)
Listed firm	-51.787***	-1.220
	(10.041)	(16.363)
Rated firm	-68.104***	-63.030***
	(7.458)	(14.793)
Asset tangibility ratio	-0.302**	0.222
	(0.150)	(0.311)
Subsidiary	-80.841***	-23.294
	(9.875)	(18.027)
Issuer controls	Yes	Yes
PDP issue controls	Yes	Yes
Year F.E.	Yes	Yes
Industry F.E.	Yes	Yes
Country F.E.	-	Yes
Mean of dependent variable	578.92	501.29
Observations	3,492	1,160
R-squared	0.564	0.531
Adjusted R-squared	0.559	0.490

Table IV: Information asymmetry, maturity and collateral

The table shows coefficient estimates and standard errors of fixed-effects OLS regression models. The sample for all columns includes 4,652 non-bank, non-public, corporate PDPs by 1,691 non-financial issuers between 1999 and 2016 globally. The dependent variable in columns 4.1-4.4 is maturity measured in years. The dependent variable in columns 4.5-4.8 is collateral which is a binary variable taking the value of 1 of the issue is secured and 0 otherwise. Listed firm is a dummy variable equal to 1 if the issuer is publicly listed on a stock exchange and 0 otherwise. Rated firm is a dummy variable taking the value of 1 if the firm has a credit rating by S&P and 0 otherwise. Asset tangibility ratio is the ratio of property, plant and equipment to total assets measured in percent. Subsidiary is a dummy variable taking the value of 1 if the issuer is not the same legal entity as the corporate parent and 0 otherwise. PDP issue controls include: maturity measured in years (columns 4.5-4.8 only), offering amount in USD millions, seniority level coded from junior to more senior levels and collateral which is a dummy variable taking the value of 1 if the issue is secured and 0 otherwise (columns 4.1-4.4 only). Issuer controls refer to a set of lagged financial control variables at the issuer level including revenues in USD millions, EBITDA margin in percent, leverage (debt to capital ratio) in percent, issuer role (e.g., sales-focused entity versus production entity) defined as the ratio of an entity's revenues to its corporate parent revenues measured in percent as well as EBIT to interest expense in multiples. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Full sample				Full sample			
	(4.1)	(4.2)	(4.3)	(4.4)	(4.5)	(4.6)	(4.7)	(4.8)
Listed firm	-0.919***	-0.843***	-0.776***	-0.721***	-0.020**	-0.018*	-0.013	-0.015
	(0.269)	(0.268)	(0.268)	(0.275)	(0.010)	(0.010)	(0.010)	(0.010)
Rated firm	1.212***	1.315***	1.027***	0.939***	-0.036***	-0.025***	-0.030***	-0.038***
	(0.210)	(0.210)	(0.212)	(0.214)	(0.008)	(0.008)	(0.008)	(0.008)
Asset tangibility ratio	0.027***	0.027***	0.020***	0.020***	-0.000**	-0.000***	-0.000**	-0.000
	(0.004)	(0.004)	(0.004)	(0.004)	(0.000)	(0.000)	(0.000)	(0.000)
Subsidiary	0.225	0.153	-0.115	-0.179	0.013	0.005	0.005	-0.008
	(0.268)	(0.268)	(0.271)	(0.277)	(0.010)	(0.010)	(0.010)	(0.010)
Issuer controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
PDP issue controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	-	Yes	Yes	Yes	-	Yes	Yes	Yes
Industry F.E.	-	-	Yes	Yes	-	-	Yes	Yes
Country F.E.	-	-	-	Yes	-	-	-	Yes
Mean of dependent variable	9.42	9.42	9.42	9.42	0.11	0.11	0.11	0.11
Observations	4,652	4,652	4,652	4,652	4,652	4,652	4,652	4,652
R-squared	0.058	0.074	0.091	0.130	0.556	0.575	0.579	0.588
Adjusted R-squared	0.055	0.069	0.0835	0.113	0.555	0.572	0.575	0.580

Figures

Figure I: Annual debt issuance over time

The figure shows the annual issuance volume (measured in USD bn) of PDPs (blue bars) and public, corporate debt (gray bars) raised in the United States between 2006-2018 (Private Placement Monitor (2019); SIFMA (2018b)). Moreover, the growth of annual issuance (measured in percent) between 2006-2018 is shown for PDPs (blue line) and public, corporate debt (gray dashed line) with a baseline in 2006.

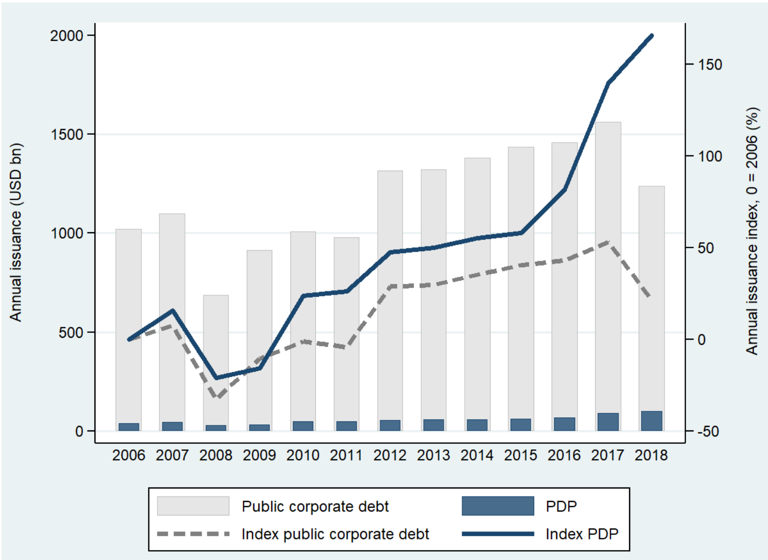


Figure II: Benchmark spread by listing/ rating status

The figure shows a descriptive comparison of the average benchmark spread incurred for 4,652 non-bank, non-public, corporate PDPs by 1,691 non-financial issuers between 1999 and 2016 globally by listing/ rating status. Benchmark spread (measured in basis points) is defined as the spread of interest rate over benchmark. Issuer firms are classified as listed if they are publicly listed on a stock exchange and as rated if the firm has a credit rating by S&P. The dark gray (dark blue) bar denotes listed and rated (non-listed and rated) firms. The light gray (gray) bar denotes listed and non-rated (non-listed and non-rated) firms.

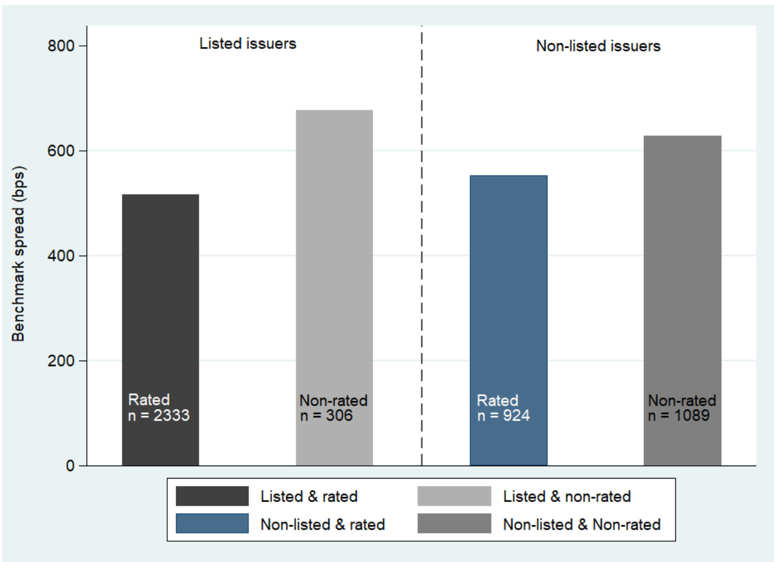


Figure III: Benchmark spread by entity type and listing/ rating status

The figure shows a descriptive comparison of the average benchmark spread incurred for 4,652 non-bank, non-public, corporate PDPs by 1,691 non-financial issuers between 1999 and 2016 globally by entity type (corporate parent versus subsidiary) and listing status. Benchmark spread (measured in basis points) is defined as the spread of interest rate over benchmark. Issuer firms are classified as listed if they are publicly listed on a stock exchange and classified as subsidiaries if the issuer is not the same legal entity as the corporate parent. The dark gray (dark blue) bar denotes listed corporate parents (subsidiaries). The light gray (gray) bar denotes non-listed corporate parents (subsidiaries).

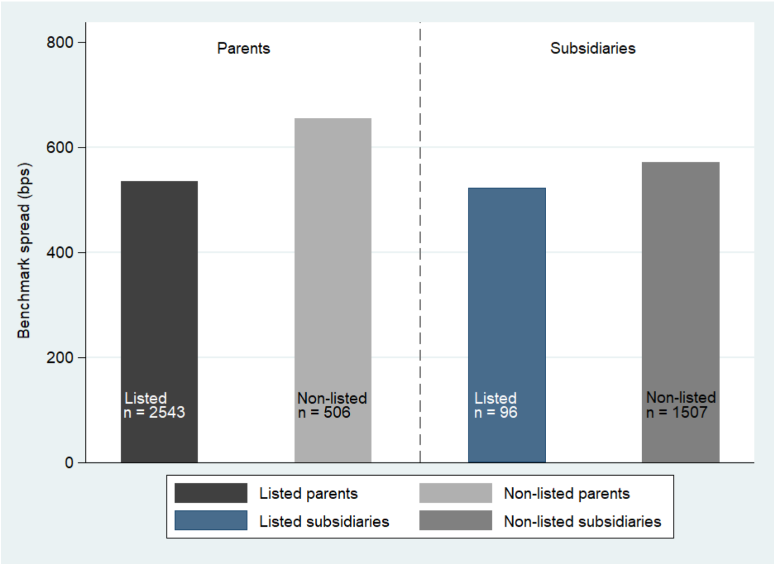
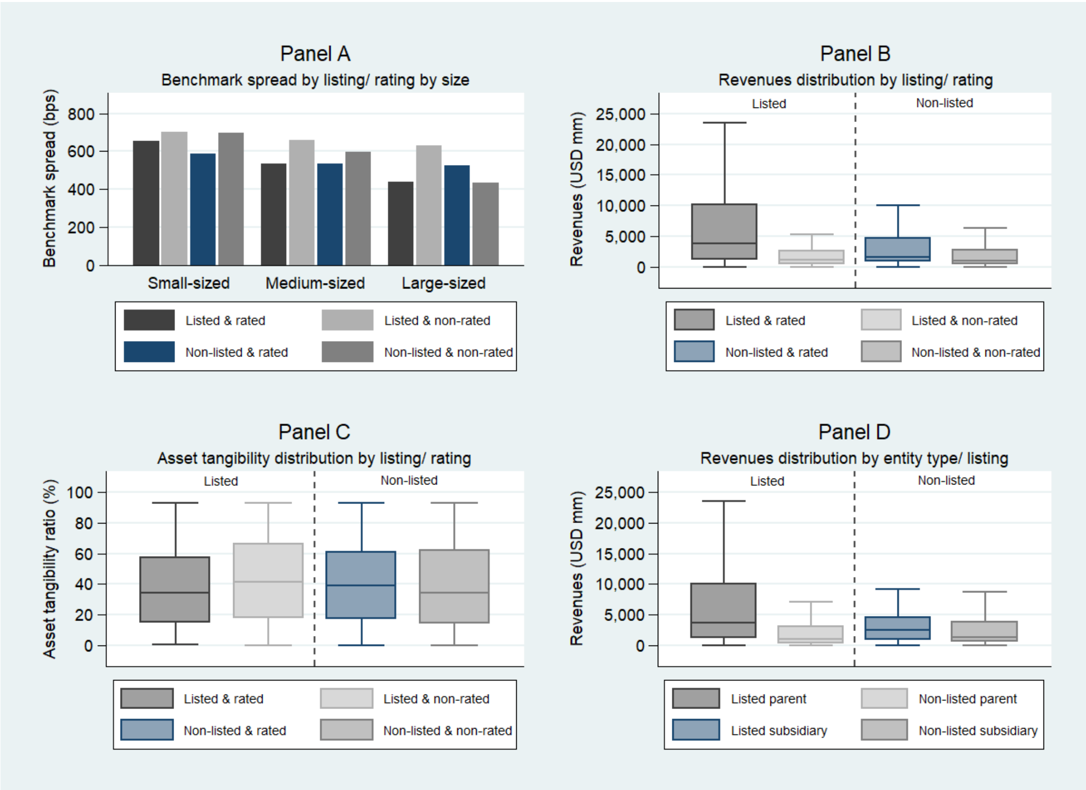


Figure IV: Relation of listing/ rating status with benchmark spread, firm size and asset tangibility

The figure shows descriptive analyses of the relation of listing/ rating status with benchmark spread, firm size and asset tangibility for 4,652 non-bank, non-public, corporate PDPs by 1,691 non-financial issuers between 1999 and 2016 globally. Benchmark spread (measured in basis points) is defined as the spread of interest rate over benchmark. Firm size (measured in USD mm) is defined as revenues. Asset tangibility (measured in percent) is defined is the ratio of property, plant and equipment to total assets. Issuer firms are classified as listed if they are publicly listed on a stock exchange, as rated if the firm has a credit rating by S&P and as subsidiaries if the issuer is not the same legal entity as the corporate parent. Panel A shows the average benchmark spread by listing/ rating status by lower, medium and upper tertile rank. The dark gray (dark blue) bar denotes listed and rated (non-listed and rated) firms. The light gray (gray) bar denotes listed and non-rated (non-listed and non-rated) firms. Panel B shows the distribution of revenues by listing/ rating status. The dark gray (dark blue) box denotes listed and rated (non-listed and rated) firms. The light gray (gray) box denotes listed and non-rated (non-listed and non-rated) firms. Panel C shows the distribution of asset tangibility by listing/ rating status. The dark gray (dark blue) box denotes listed and rated (non-listed and rated) firms. The light gray (gray) box denotes listed and non-rated (non-listed and non-rated) firms. Panel D shows the distribution of revenues by entity type/ listing status. The dark gray (dark blue) box denotes listed corporate parents (subsidiaries). The light gray (gray) box denotes non-listed corporate parents (subsidiaries). For all box plots, outlier values are not displayed.



Client satisfaction and firm performance: The impact of social media on bank branches

Kilian R. Dinkelaker [a]

Abstract

Employing a novel dataset entailing more than 5 million reviews on Yelp.com, I explore the association between consumer ratings of bank branches and their deposit growth. I ascertain that higher consumer ratings are positively correlated with stronger deposit growth. However, a regression discontinuity analysis exploiting discrete steps in ratings does not confirm a causal impact of ratings on deposit growth. The results equally inform bank management and legislators given the looming regulation of social media.

Keywords: *Bank deposits, monitoring, location-based social networks, consumer reviews*
JEL classification: D11, D16, G21, G41, E21

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I. Introduction

Social media has become an important channel for the interaction between businesses and customers. Empirical evidence regarding the effect of social media user ratings on business turnover has been documented in extant research. For example, Anderson and Magruder (2012) and Luca and Zervas (2016) investigate the retail services sector and the hospitality business in particular. These authors establish a role of social media networks both as vehicles for consumer feedback and as centralized monitoring platforms for the broader public. Such influence is among the reasons which have prompted regulators to envisage stricter regulation of social media (Waterson (2018)).

However, it is unclear whether social media also has a similar impact on business outcomes in other retail services sectors. There is no empirical research to date regarding the effect of consumer ratings on financial service providers. This is astonishing given the pronounced contribution of the financial services sector to the economy (Greenwood and Scharfstein (2013)). In the United States, this sector accounts for almost 10% of GDP, which is on par with the manufacturing sector and higher than the retail and construction sectors (BEA (2018b)).

The lack of research is also surprising given that the above-mentioned concept of monitoring through social networks is indeed established in the area of financial services research. Theory foresees that banks which can be considered key components of the financial system act as intermediaries and delegated monitors. At the same time, the necessity of monitoring the actions of banks themselves to avoid adverse behavior in deposit contracts can be derived from economic theories (cf. Jensen and Meckling (1976); Calomiris and Kahn (1991)). Iyer et al. (2013) argues that depositors do partly perform this monitoring role. Evidence on the monitoring of banks through non-digital social networks has also been published (e.g., Kelly and Ó Gráda (2000)). Such mechanisms remain conceivable, yet opaque for internet-based social media networks. On the other hand, prior literature has highlighted the role of switching costs in banking relationships' stickiness and the market power of banks over deposits (Kiser (2002); Drechsler et al. (2018)). These elements might weaken the influence of monitoring through networks

Taken together, the prior findings on the real economic effects of social media content and the lack of application in the area of finance mean that the research question raised can be readily summarized: Is there an association between bank branch consumer ratings in social media networks and branch-level business performance?

To answer this question, I assess the effect of "Yelp" ratings on deposit volume growth of bank branches in the United States. Yelp is a major location-based social network ("LBSN") for online consumer reviews of businesses. Deposit volume growth can be considered a performance metric indicating, e.g., whether depositors are entrusting their funds to the bank (branch). Controlling for bank, county and state factors, the effect of being highly and lowly rated on Yelp compared to not being rated will undergo further investigation. The purpose of this is to address the likelihood of a sample bias. The above-mentioned research effort relies on the first and most comprehensive location-based social media dataset utilized in financial intermediation research to date. The location-based social network dataset in the scope of this study stems from the leading player in the United States and features branch- and user-level data. It includes more than 5 million reviews on businesses in total. Among a limited number of other options, I select this particular LBSN as - in contrast with others - it entails both location data and structured consumer reviews.

My main findings are as follows: First, 0.5 more Yelp rating "stars" on a rating scale from 1-5 are associated with a 1 p.p.[1] higher deposit volume growth. This corresponds to USD 1 million deposited at a bank branch in a year in addition to the average annual deposit volume growth of USD 10 million. Second, this effect appears to be driven by the higher Yelp rating categories and is not driven by a sample effect of being listed in Yelp per se. These results are stable across a variety of specifications including control variables and a set of fixed effects. However, third, the RDD approach does not support the inference of a causal relationship between Yelp ratings and deposit volume growth.

The contribution of this study is threefold. First, I add to the existing literature on business outcomes induced by LBSNs. Primarily, Yelp and "TripAdvisor" data is employed by Luca (2016) and Mayzlin et al. (2014), respectively. These authors examine the effect of Yelp ratings on restaurant revenues as well as of the drivers of review fraud on TripAdvisor. Luca (2016) shows that a one-star increase in the Yelp rating of restaurants is associated with an increase in their revenues of 5-9%. Anderson and Magruder (2012) is another example of analyzing LBSNs as crowd-based monitoring platforms. The authors identify a positive impact of higher Yelp restaurant ratings on demand for table reservations.

My study is the first of its kind to focus on the financial services sector rather than the hospitality sector. Moreover, the study at hand uses a measurably larger and more recent Yelp dataset covering substantially more geographic areas, rather than one city as has been the case in prior research. Previously-used datasets also date back to roughly 2013 or earlier, containing substantially fewer reviews and users, as well as a lower number of variables. It should be noted that adoption of LBSNs was also measurably less developed in these years.

The second literature stream which this study aims to extend scrutinizes the drivers of bank (branch) performance. One performance indicator discussed by various papers is bank runs caused by the banks' adverse behavior or poor management. Examples include Kelly and Ó Gráda (2000) and Iyer et al. (2016). Based on theory by Chari and Jagannathan (1988) referring to Diamond and Dybvig (1983), the aforementioned authors identify the flow of information (actual facts versus panic) through (non-digital) social networks ("contagion", cf. Chari and Jagannathan (1988), p.749) as a monitoring force behind bank runs.

While the data used for this study allows for an analysis of a higher number of banks, it also focuses on the more general, everyday depositing and withdrawing behavior as a nuanced view in addition to bank runs. Moreover, I focus on disciplining exercised by consumers with regard to bank service provision rather than the adverse incentives of the banks. I also address one data challenge encountered in many bank run papers to date

[1]Percentage points.

which are usually restricted to depositor data from one bank or survey data which does not track actual behavior. Apart from the fact that the LBSN dataset envisaged for this study covers the near-universe of retail banks and a high share of their branches in the sample cities, it should allow for a more accurate reconstruction of consumer activities. It also goes beyond the perspective of deposit withdrawal statistics of many prior datasets by scrutinizing the overall growth of deposit volumes at the bank branch level. To my knowledge, this remains a research question which must be answered. Thereby, I also shed light on the monitoring role of consumers given the well-established theories (cf. Calomiris and Kahn (1991)).

Third, extant literature assesses specific social messaging and information exchange platforms regarding their effects within certain investor and trading communities. This stream shows that content on social trading platforms such as “SeekingAlpha” (Chen et al. (2014)) and messaging networks such as “Twitter” (Bartov et al. (2017), Blankespoor et al. (2013)) can help predict stock returns and earnings and correlates with bid-ask spreads. Once more, these authors affirm that information originating from social networks influences economic outcomes.

The present study does not only add to this discussion by using structured and quantifiable ratings rather than textual data. My research question is also more geared toward effects for the general public rather than toward specific parts of the finance community. This is enabled by data from one of the most widely-used LBSNs, which is also among the most popular websites in the United States in general.

The remainder of this paper proceeds in the following manner: Section II describes the institutional environment of bank branches and LBSNs. Section III presents my data in detail. Empirical results and robustness tests are reported in Section IV. Section V concludes.

II. Institutional environment

According to the International Monetary Fund Financial Access Survey (2018), there are 31.46 commercial bank branches per 100,000 adults in 2017 in the United States[2]. Comparing the latter with other developed economies, the United States range exhibit a similar coverage like observed for Australia and Japan (29.60 and 34.02). The figure is relatively lower than the number of branches in Switzerland or Italy (40.73 and 44.62), but larger than in Germany and Canada (12.89 and 21.47).

Past legislation on branch banking[3] has resulted in a major shift of the branch land-

[2] In total, there were approximately 79,000 branches in total at the end of 2017 (FDIC (2018a)).

[3] Several key statutes constitute the legal framework with regard to branch banking. First of all, the National Bank Act of 1863 created the foundations of the banking system in the United States (Agrawal Sahni and Byrne (2018)). It also included restrictions on interstate branch banking by nationally chartered banks. The Banking Act (also referred to as “Glass-Steagall Act”) signed into law in 1933 created a federal deposit insurance system in an attempt to maintain trust in the financial system (Maues (2013)). The previously introduced ban on out-of-state acquisitions of banks and bank holding companies was further reinforced by the Bank Holding Company Act of 1956 (Jayaratne and Strahan (1996)). Following several state-level relaxations of interstate banking restrictions, the Riegle-Neal Interstate Banking and Branching Efficiency Act of 1994 allowed acquisitions by banks in other states upon approval by the respective state. Another major part of currently applicable legislation was passed in 2010, namely the Dodd-Frank Wall Street Reform and Consumer Protection Act. One aspect of the laws included herein pertains to new consumer protection measures, e.g., in the area of credit cards (cf. Agarwal et al. (2014)),

scape toward the emergence of several major nationwide banking players maintaining an interstate branch presence. The largest market share of deposits is held by J.P. Morgan Chase Bank, Wells Fargo Bank and Bank of America (FDIC (2017)). Of note, no significant regulatory initiative concerning branch banking came into force during the time frame in scope of this study.

Whilst the underlying trend of a decreasing number of bank branches seems irreversible, a differentiated pattern appears to hold with regard to the role and number of bank branches in the United States economy. On the one hand, the advent of online banking technologies is considered a major driver for closure of bank branches (Tranfaglia (2018)). Recent data has revealed that two thirds of adults in the United States are primarily using internet and mobile channels to manage their bank accounts (ABA (2018)). Whereas less than 20% prefer going via a bank branch. On the other hand, major banks including Bank of America and J.P. Morgan Chase have recently announced plans to open several hundreds of new branches in urban areas within the next years (Henry and Subba (2018)). Furthermore, despite the increasing adoption of internet technologies for banking purposes, this should be seen in the broader context of consumer payment methods. Their usage has been rather stable over time as shown in a survey (Greene and Stavins (2018)). Traditional payment types such as cash, credit/ debit cards and paper checks remain the most frequently used ways to pay, accounting for approximately 90% of consumer payments. Cash and paper checks in particular would often require physical points of service, e.g., bank branches or automated teller machines. Checks also continue to be an important tool for paying invoices between businesses. In 2016, roughly 50% of business-to-business transactions in the United States were made using checks (AFP (2016)). Compared to other continents, both the share and the number of check transactions are considerably higher.

Taking these developments together, the number and density of bank branches currently still indicates an important function for both individuals and businesses. This importance also pertains to banks themselves. (Retail) deposits are of considerable importance for bank financing, more than other instruments such as interbank lending. Recent call report data by the Federal Deposit Insurance Corporation (“FDIC”) (2018b) has shown a stable share of retail deposits on the liability side of United States banks’ balance sheets. More than 75% of banks’ liabilities were deposits at the end of 2017 and retail deposits constituted almost two thirds of the total deposit volume of banks (FDIC (2018b)). Other major types of liabilities have a lower share. Depositor behavior can therefore be assumed to be a driver of bank branch deposit volumes. At the same time, the growth of bank branch deposits exhibits a high variation as shown in Figure I. Drivers of this variation of this important source of bank financing remain to be explained. This provides motivation for the study at hand.

- Figure I about here: Distribution of bank branch deposit volume growth -

disclosure of deposit interest rates and fees (Agrawal Sahni and Byrne (2018)) and financial advice. However, Section 613 of the act also abolished the requirement of state approval for interstate banking as laid out by the Riegle-Neal Act (Mayer Brown (2010)). In consequence, banks from any state are now allowed to branch into any other state which has led to the formation of several major nationwide banking players active across state boundaries.

As for characteristics of social media, they have overtaken traditional media channels such as television or newspapers in terms of consumption time growth (AMA (2015)). Apart from platforms with a general focus on social networking, e.g., Facebook, there are various other types. Certain social media networks can be classified as LBSNs such as, e.g., Yelp and Foursquare. These are at the center of this study. In general, LBSNs allow users to share their current location via a "check-in" (also referred to as "geotagging" (Turner (2006), p.4) with other users in the same social network and those users flagged as "friends" in particular. Some LBSNs are also integrated with other non-location-based social networks such as Facebook where check-ins can be shared with further social audiences. Based on the GPS location of users transmitted by their mobile phone, the LBSN verifies the location. In addition to merely checking in at certain places, some LBSNs allow users to leave comments concerning the location. These comments range from a text field for plain sentences to structured consumer reviews.

In the case of Yelp[4] which is the LBSN in scope for this study, consumer reviews are at the core of the service. Once logged in on Yelp, users can look up detailed profiles of a vast range of businesses of almost any type in many cities around the globe, check in and/ or leave a review. Businesses listed on Yelp include restaurants, shops, bank branches and most kinds of services which are provided from a physical location. The review has two components. A "star" rating from 1 star (worst experience) to 5 stars (best experience) derived from the arithmetic mean user rating for a business is accompanied by a comment functionality with photo upload. Based on these ratings, Yelp applies the average of all consumer reviews rounded to half increments. The business' address, map-based directions, opening hours, details on its facilities such as parking lot availability and photos of the location are further parts of profiles on Yelp. Please refer to Figures II, III and IV for a sample of the Yelp search function and screenshots of a Yelp profile of a bank branch.

- Figures II, III and IV about here: Sample illustrations of the LBSN "Yelp" -

According to Yelp (2018f), this LBSN entailed cumulative 170 million reviews in the third quarter of 2018. The Yelp website has a significant reach, especially in the United States. It is ranked 43rd in the United States and 210th globally of all websites in terms of monthly unique visitors in December 2018 according to Alexa (2018) statistics. Both from desktop computers and mobile applications, Yelp had approximately 70 million unique visitors in 2016 (Yelp Inc. (2018e)). In terms of age and income, Yelp user demographics pertaining to the entirety of users are fairly balanced (Yelp Inc. (2018d)). About one third of users each is between 18-34, 35-54 and 55 and more years old, respectively. Higher-income users (more than USD 100,000 earned annually) represent less than 50% of users. About one quarter of users earns up to USD 59,000 p.a. and USD 60,000-99,000 p.a. Whereas in terms of educational background, more than 60% of Yelp users have a college degree. 20% have a graduate school background and the remaining 20% have a

[4]Founded in 2004, Yelp (https://www.yelp.com) is a public company listed on the New York Stock Exchange (NYSE: YELP) with a market capitalization of approximately USD 2.8 billion in December 2018 (Google Finance (2018)) and revenues of USD 847 million in 2017 (Yelp Inc. (2018e)).

high school degree. Therefore, together with its closest competitors Google Reviews[5] and "TripAdvisor"[6], Yelp can be considered among the major, wide-spread LBSNs globally. Hence, it is particularly interesting for this study.

III. Data

A. Data sources

This study relies on two data sources. My main source is a novel LBSN dataset by Yelp which has been officially provided by the company itself[7]. Less extensive predecessors of this Yelp dataset have been used in prior economics and management literature (e.g., Luca and Zervas (2016)). This dataset is complemented by data on bank branch deposit volume and further bank (branch)-related control variables published by the FDIC. FDIC data is utilized in numerous instances of finance literature (e.g., Ashcraft et al. (2005); Cornett et al. (1998)).

In contrast with various publicly available datasets covering other LBSNs, the data at hand is not "crawled" or "scraped" by individual researchers (e.g., data obtained from "Foursquare" by Yang et al. (2014)). These methods are very common in information systems and machine learning research. However, their methods may be less apparent to secondary users. With almost 5 gigabytes of data in "JSON"-format, this Yelp dataset is among the most extensive ones of social media available for academic research to the best of my knowledge. Covering reviews for businesses in mostly United States and a few European metropolitan areas[8], it entails reviews and check-ins by 1.3 million unique users for more than 170,000 businesses. Overall, the sample features more than 5 million consumer reviews, i.e., ratings of businesses. Address at street and ZIP code level and overall rating are variables available for each business in the sample. I focus the analysis on the United States since usage of Yelp is most wide-spread and the number of non-United States cities per country in the sample is rather low[9].

As far as the deposit volume data by the FDIC is concerned, this United States federal agency offers publicly accessible datasets on financial institutions which include lists of all institutions and their branches. The aim is to reconstruct deposit volume growth rates parallel to a timeline of consumer reviews obtained from the LBSN data discussed above. I employ two datasets provided by the FDIC: First, deposit volumes at the branch level of FDIC-insured banks have been documented on an annual basis and are updated by the end of June each year ("Branch Office Deposits - Summary of Deposits" file). Second, various financial and operational variables are available at bank institution level.

[5] Yelp and Google reviews are the most commonly used online review sites in the U.S. according to a survey by Podium and Statista (Podium (2017)).

[6] TripAdvisor is focusing on travel reviews. As opposed to Yelp, it does not feature ratings of bank branches.

[7] Information regarding the research question and purpose of this study was not available to Yelp prior to selection of the dataset at hand.

[8] Major cities included: Pittsburgh, Phoenix, Las Vegas, Madison, Cleveland (all United States), Montreal (Canada), Waterloo (Canada), Edinburgh (UK), Karlsruhe (Germany).

[9] Please refer to the sections below for details on the final sample.

B. Sample construction

Yelp includes entries for virtually any business with a physical location. Roughly 4,250 financial service firms constitute 2.5% of the rated entities. This also includes mortgage brokers and loan service providers. Roughly 1,000 businesses are bank and credit union branches[10] of which 683 bank branches in 2016 remain in the final sample.

As the Yelp review and FDIC deposit volume data do not rely on the same unique identifiers[11], the two datasets have to be matched manually. This matching is performed by utilizing the branch street address, city name, ZIP code, county, federal state and geographic latitude/ longitude which both Yelp and FDIC provide for each branch. As an additional check, the existence of each branch at its respective street address is verified using the branch locator features on the individual banks' websites. In the next step, individual Yelp user ratings and their time stamps are added to each bank branch entry. Information pertaining to individual Yelp users is aggregated at bank branch level using the IDs for reviews and users assigned by Yelp's SQL-structured data. In addition, the annual deposit volume growth rate of each branch is obtained by calculating the change in deposit volume from one year to the next in percent. Figures II, III and IV present details on the way Yelp presents bank branch entries and corresponding consumer reviews.

C. Descriptive statistics

Arriving at a final sample comprised of 683 rated bank branches by 55 banks in 2016, Bank of America, J.P. Morgan Chase Bank and Wells Fargo Bank together operate 66% of bank branches in the sample. This is consistent with their market share (cf. FDIC (2017)). All nine metropolitan areas in seven federal states and twelve counties covered by the Yelp dataset, namely Charlotte (NC), Cleveland (OH), Columbus (OH), Las Vegas (NV), Madison (WI), Philadelphia (PA), Phoenix (AZ), Pittsburgh (PA) and Urbana-Champaign (IL) are included in the sample. Figure V presents the geographic distribution of these regions. The data coverage tends to be more toward the East Coast and Midwest of the United States and focuses on urbanized areas. Whilst two metropolitan areas exhibit a number of inhabitants of below 1 million (Madison and Urbana-Champaign), greater Philadelphia and Phoenix have the highest number of inhabitants. 33% of all FDIC-registered branches in the sample cities have a consumer rating on Yelp and so have 25% in the sample counties. I provide details on differences between Yelp-rated and non-rated bank branches subsequently.

- Figure V about here: Geographic coverage of the Yelp dataset -

Table I reveals further detail regarding the socioeconomic characteristics of the sample metropolitan areas[12], offering a perspective on representativeness in comparison to

[10] Credit Unions were excluded from the sample due to limited branch-level deposit volume data provided by the United States Federal Credit Union Administration.

[11] Yelp uses a 22-character non-human-readable string ID whereas FDIC has a unique ID number for each branch.

[12] As described in Section II, the community of Yelp users represents all age, education and income groups (Yelp Inc. (2018d)). A concentration on particularly young and internet-savvy users cannot be inferred from overall user demographics.

national average figures. Based on 2017 GDP figures (BEA (2018a)), the sample areas are substantially larger than other metropolitan areas, on average. At the same time, they include both low and high GDP level areas. The 2017 GDP per capita is above the national average. Concerning GDP growth from 2016-2017 (BEA (2018a)), the rates are dispersed around the national average. Pittsburgh grew fastest by almost 4% while Urbana-Champaign almost stagnated. None of the metropolitan areas is found to be in recession. The average unemployment rate in 2018 (BLS (2018)) resembles the average rate observed in country-wide metropolitan areas. 2016 population age average and median (USCB (2016)) range around 33 years. 2013 broadband/ mobile internet usage (Tolbert and Mossberger (2018)) is above average.

I conclude that metropolitan areas covered in the Yelp sample exhibit a tendency toward a younger, more internet-savvy population. The areas are also among the larger urban agglomerations to find. As far as economic growth, GDP per capita and unemployment are concerned, it can partially be asserted that these metropolitan areas are more prosperous than the rest of the country. The sample rather seems to be balanced in terms of economic indicators, taking all of them together. Neither does the sample include outlier regions such as the San Francisco bay area nor does it exclude "rustbelt" cities.

- Table I about here: Socioeconomic characteristics of geographies covered -

In terms of bank branch-related variables for 2016, as shown in Table II, the average number of branches per bank is just above 10 with a median of 1. The average Yelp rating of bank branches is 2.86 with a median of 3. Ratings tend to be more skewed toward the upper half of the Yelp rating scale[13]. Sample data regarding the number of Yelp reviews received by individual bank branches is also reported in Table II. The rating score of bank branches is based on 4.39 Yelp reviews on average and a median of 3.

- Table II about here: Summary statistics - Characteristics of bank branches and Yelp reviews -

The distribution of the number of Yelp reviews is rather centered as shown in Figure VI. Given that businesses with Yelp ratings worse than 4 are typically considered less recommendable based on anecdotal evidence and user observations, I aggregate Yelp rating classes into "bad ratings" (1-3.5) and "good ratings" (4-5). Branches with bad ratings receive more Yelp reviews and this difference is statistically significant.

- Figure VI about here: Number of Yelp consumer reviews by Yelp rating category -

[13] Yelp reviews might partially suffer from false reviews either inflating reviews upwards or downwards. As depicted by Luca and Zervas (2016), the company is relying on algorithms to detect and remove false entries. Despite the fact that such an algorithm might not work perfectly, it is likely to detect a high share of inflated reviews. Further, the success of service providers like Yelp is to a large extent contingent on the reputation of its content. The long history of Yelp and the growing number of users speaks in favor of the overall accuracy of user activity registered by the LBSN. As shown in Section IV, the results of this study appear not to be driven by inflated ratings.

Table III reports information regarding review quality and reviewers consolidated at branch level. Among those 2,675 reviewers having rated a bank branch on Yelp, on average, less than one reviewer is part of Yelp's "Elite squad"[14]. Members of this reward scheme make up 11.8% of bank branch reviewers while 15.7% of reviews are authored by elite users. Both in terms of average and median, bank branch reviewers had been registered on Yelp for approximately four years. As another proxy for reviewer activity, the average reviewer had posted approximately 185 reviews on Yelp in total assigning an average rating of 3.48 which is higher than the average bank branch rating in the sample. The number of those reviewers in the sample repeatedly exhibiting a negative attitude in their reviews of bank branches and businesses in general amounts to 24. This explains the low average number of less than 0.1 per bank branch.

- Table III about here: Summary statistics - Characteristics of reviewers -

Table IV depicts the distribution of both deposit volume and deposit growth (June 2016-June 2017)[15] of bank branches in the sample of 683 Yelp-rated branches. Figures of all other bank branches within the same *cities* of Yelp-rated branches and of all other bank branches within the same *counties* of Yelp-rated branches are included. In total, there are 2,745 branches in the counties covered by Yelp of which 683 are Yelp-rated. Those branches which have received a Yelp rating hold, on average, about USD 110 million in deposits. Yelp-rated branches are approximately 60% larger in terms of mean and median when looking at deposit volume than those which are not Yelp-rated. Taking a closer look at the deposit volume of branches by Yelp rating class, branches with medium ratings (2-3.5) are larger than the lower end of the Yelp rating scale (1-1.5 and 4-5). The difference in average and median deposit volume of branches in good and bad rating categories (1-3.5 vs. 4-5) is small and there is also no statistically significant difference as indicated by the t-value.

- Table IV about here: Summary statistics - Characteristics of bank branch deposit volume -

With respect to deposit volume growth (Table V), Yelp-rated bank branches have, on average, witnessed deposit growth of 12.2% p.a. This corresponds to about USD 10 million in terms of the absolute amount. The mean deposit volume growth of branches without a Yelp rating is approximately 2 p.p. lower. In terms of median, the difference amounts to approximately 3 p.p. I conclude that there is a structural difference between Yelp-rated and non-rated branches regarding deposit volumes. As far as the deposit volume growth rate is concerned, the discrepancy is less pronounced.

- Table V about here: Summary statistics - Characteristics of bank branch deposit volume growth -

[14] Yelp's reward scheme for the most active users. User can obtain this status, e.g., through regular review activity, photo uploads etc. Elite users receive a badge icon shown on the user profile.

[15] Please note that the FDIC only reports branch-level deposits once annually as per 30th of June.

Figure VII visualizes the deposit volume growth figures of bank branches by Yelp rating category. It also demonstrates that only bank branches in the highest rating categories experience growth higher than the average rate of the sample of Yelp-rated branches. Higher rated branches appear to have higher deposit volume growth than lower rated ones. The difference is statistically significant. Deposit volume growth increases monotonically from lower to higher rating brackets.

- Figure VII about here: Bank branch deposit volume growth by Yelp rating category -

IV. Empirical results

The growth rate of bank branch deposit volume from June 2016 to June 2017 measured in percentage points is the dependent variable for all regression models. The core explanatory variable is the Yelp rating as such measured in 0.5 increments from 1 (worst) to 5 (best) (Section IV-A.1). Second, we use the category of a Yelp rating for bank branches (Section IV-A.2). And third, we use the annual change of Yelp ratings (Section IV-A.3). The empirical strategy is based on fixed effects OLS regression models as well as a RDD framework (following Anderson and Magruder (2012), Luca (2016) and Lee and Lemieux (2010)) discussed in Section IV-B.

The main identification challenges of this set-up are posed by potential omitted variables and reverse causality between my dependent and explanatory variables. As an example for the first issue, other factors than the observable ones such as specific promotional activities or behavior by branch staff might be driving deposit volume growth. In order to extenuate this concern, this study relies on a broad range of control variables and fixed effects for bank (branch), review, reviewer and location characteristics. As an example for the second above-mentioned issue, the bank headquarters could decide to extend the service offering of a strongly growing branch which in turn leads to improved depositor satisfaction and therefore improved ratings on Yelp. For this reason, both lagged explanatory and control variables are employed for the subsequent analyses to circumvent this endogeneity concern. For instance, Yelp ratings are measured before the beginning of the dependent variable's observation period

A. Yelp ratings and bank branch deposit volume growth

A.1. Yelp rating

In the first part of the analyses, I focus on Yelp ratings and deposit volume growth of bank branches. The baseline specification applied in order to verify this association can be expressed as follows:

$$\begin{aligned} Bank\,branch\,deposit\,growth_{i,b,c,s\,2016/2017} &= \alpha_b + \alpha_c + \alpha_s + \beta_1 \times Yelp\,rating_{i,b,c,s} + \\ &\quad \beta_n \times X_{i,b,c,s} + \beta_n \times Z_{r,i,b,c,s} + \varepsilon_{i,b,c,s} \end{aligned} \tag{1}$$

The dependent variable, Bank branch deposit growth$_{\text{i,b,c,s 2016-2017}}$, is the percentage change in deposits from June 2016 to June 2017[16] of each individual bank branch i of bank b (i.e., the institution a branch belongs to) in county c in federal state s as reported by the FDIC. α_b, α_c and α_s are bank, county and state fixed effects accounting for the potentially endogenous influence bank-, county- and state-related factors. β_1 is the estimated effect of my core explanatory variable, the Yelp rating of a bank branch in June 2016, on Bank branch deposit growth$_{\text{i,b,c,s 2016-2017}}$. The Yelp rating is measured from 1 to 5 in 0.5 increments.

Control variables available at bank branch level are summarized in vector $\text{X}_{\text{i,b,c,s}}$. These lagged branch-related control variables include the time a bank branch has been operating measured in years, the number of reviews received by each branch and the deposits held by each branch at the beginning of the observation period in June 2016. For example, rather than the Yelp rating, the mere number of reviews might influence depositors' decisions as they might be more receptive to increased transparency as such than the actual rating. Likewise, branches with a long-standing history might be located in areas with less dynamic economic growth as opposed to newer branches benefiting from new wealth creation. In addition, it might rather be the bank's overall reputation driving new deposits with the individual branch having limited influence. Control vector $\text{Z}_{\text{r,i,b,c,s}}$ encompasses lagged control variables for review quality, reviewer activity and heterogeneity. They entail the number of Yelp "Elite" reviewers who have rated a bank branch which is defined as the number of all Yelp reviewers with "Elite squad" status in 2016 and/ or 2015. The average reviewer number of "useful" review tags received by all reviewers of a bank branch and the average reviewer Yelp usage tenure since registration is also included. Moreover, the average reviewer number of Yelp reviews (average number of Yelp reviews of all reviewers of a bank branch) measures activity. The average reviewer Yelp rating is part of the control variables for reviewer heterogeneity. Lastly, the variable "number of negative attitude reviewers" intends to capture further differences in rating behavior. The variable is defined as the number of reviewers of a bank branch who a) have, overall, assigned average Yelp ratings of below and equal to 2.5 and b) have assigned average Yelp ratings of below and equal to 2.5 to bank branches.

Table VI reports a statistically significant effect of Yelp ratings on bank branch deposit volume growth for the Yelp-rated branches in scope in all columns. As the Yelp rating is measured in nine half-star rating steps from 1 to 5, and deposit volume growth is measured in percentage decimals (1% = 0.01), the coefficients can be interpreted such that a half-star difference in Yelp rating is associated with an approximately 1 p.p. higher deposit growth rate (cf. column 6.1 and 6.2). Statistical significance levels range from 1% to 10%. This result is robust to the choice of fixed effects which have been added for bank, county and federal state. The overall results are also stable when subsequently adding review and reviewer control variables (columns 6.7-6.12).

- Table VI about here: Yelp ratings and deposit volume growth -

[16] Please note that the FDIC only reports branch-level deposits once annually as per 30th of June.

Prior literature has discussed extreme Yelp ratings at the lowest and highest end of the rating spectrum (cf. Luca and Zervas (2016)). To show that the results are not influenced by the highest- or lowest-rated branches, a subsample analysis is presented in Table VII. The subsamples in columns 7.1-7.6 (7.7-7.12) exclude branches in the lowest (highest) rating class. My baseline results are confirmed.

- Table VII about here: Yelp ratings and deposit volume growth (Robustness test) -

The results of Table VI and Table VII indicate that higher Yelp ratings are associated with stronger deposit growth. Concerning the economic magnitude, the effect of a 1 p.p. higher deposit volume growth rate per half-star Yelp rating translates into approximately USD 1 million in terms of absolute growth. In light of the aforementioned average deposit volume growth of approximately USD 10 million and 12%, respectively, this points toward a measurable effect.

A.2. Yelp rating category

A potential concern to be discussed in the context of the above results is a bias in the sample of Yelp-rated banks. The selection reasons for why the Yelp-rated branches have a Yelp rating (33% of all bank branches in the cities covered by the dataset are Yelp-rated) as opposed to others are not known. Thus, any result could be driven by a sample effect. As shown in Section III, Yelp-rated branches have different characteristics than their non-rated counterparts looking at size and years of operation. Yelp-rated branches tend, on average, to hold more deposits, to be founded more recently and to exhibit slightly higher deposit growth rates. One potential scenario could be that only branches susceptible to changes in deposit growth are Yelp-rated. Alternatively, only branches attracting a particularly internet-savvy clientele might be captured by the sample. Since these aspects are unknown, the need for further testing based on the full sample of all bank branches located in the metropolitan areas covered by the Yelp data arises.

Further to this, the question as to whether high Yelp ratings are beneficial from a bank branch perspective can be analyzed in more detail using the full sample of all bank branches. Specifically, the effect of being (highly) Yelp-rated in comparison to not having a rating would be of relevance. Theoretically, bank branches might benefit as much from having no Yelp rating as from being in a high Yelp rating category. Effects due to non-rated branches would challenge the centralized monitoring which is assumed to be induced by Yelp. Consequently, the next part of the analysis will include the entirety of bank branches in counties in which Yelp-rated bank branches have been identified. This approach is expressed in the following baseline regression equation:

$$\begin{aligned} Bank\ branch\ deposit\ growth_{i,b,c,s\,2016/2017} \quad = \quad & \alpha_b + \alpha_c + \alpha_s + \\ & \beta_1 \times High\ rating\ category_{i,b,c,s} + \\ & \beta_2 \times Low\ rating\ category_{i,b,c,s} + \\ & \beta_n \times X_{i,b,c} + \varepsilon_{i,b,c,s} \end{aligned} \tag{2}$$

In this specification, β_1 is a dummy variable taking the value of 1 if a branch has a high Yelp rating of 4, 4.5 or 5 and taking the value of 0 otherwise. Low rating category (β_2) is a dummy variable equal to 1 in case of low branch Yelp ratings 1-3.5, otherwise the dummy takes the value of 0. The remaining category, "No Yelp rating" is a dummy variable taking the value of 1 if a branch had no Yelp rating in June 2016. It takes the value of 0 otherwise and it is omitted for the regression allowing to analyze the effect of a high and low Yelp rating *in comparison* to having no Yelp rating. Aiming to combine the category variables with appropriate fixed effects, I proceed as follows. I filter the full sample of all FDIC-registered branches for those banks (counties and states) entailing branches in all three rating categories in order to apply bank (county and state) fixed effects in the respective subsamples. Tables A-I and A-II in the Appendix show that the majority of counties and states do fulfill this condition whereas only 15 banks can be included in the bank fixed effects analysis. In line with highest market share banks shown in Section II, only larger banking groups operate bank branches in all three rating categories. Nevertheless, their branches represent 55.3% of all branches in the sample.

Results are shown in Table VIII. Columns 8.1 and 8.2 reveal no statistically significant result - compared to the baseline "No Yelp rating" constant - for High rating category. But the results for the Low rating category are negatively significant statistically and economically. The opposite result applies for the larger samples in columns 8.3-8.4 including county fixed effects and in columns 8.5-8.6 including state fixed effects. These columns also reveal a positive and significant constant. The remaining control variables maintain their effect on deposit volume growth. Their coefficients are either statistically or economically insignificant. In particular, coefficient estimates for bank branch deposit volume and years of operation have a high statistical significance constantly at the 1% level but there is hardly any economic effect. These results indicate that the mere fact of being Yelp-rated (low and high) is not associated with a different deposit volume growth rate as opposed to having no Yelp rating. Only one rating category in each subsample seems to influence the dependent variable.

- Table VIII about here: Yelp rating category and deposit volume growth -

A.3. Yelp rating changes

Extending the previous results on Yelp ratings, not only the static rating at a single point in time but also changes in Yelp ratings might affect the actions of depositors. Among the 620 Yelp-rated bank branches in 2015 forming the subsample for this part of the investigation, 49.6% experience a change in their rating in the period from 2015-2016. On average, ratings decrease by 0.206 rating points. The following equation illustrates the empirical approach accounting for a dynamic perspective on Yelp ratings.

$$\begin{aligned} Bank\,branch\,deposit\,growth_{i,b,c,s\,2016/2017} \;=\;& \alpha_b + \alpha_c + \alpha_s + \beta_1 \times Yelp\,rating_{i,b,c,s} + \\ & \beta_2 \times Positive\,rating\,change_{i,b,c,s\,2015/2016} + \\ & \beta_3 \times Negative\,rating\,change_{i,b,c,s\,2015/2016} + \\ & \beta_n \times X_{i,b,c,s} + \beta_n \times Z_{r,i,b,c,s} + \varepsilon_{i,b,c,s} \end{aligned} \quad (3)$$

In this specification, β_2 is a dummy variable taking the value of 1 if a branch has a positive Yelp rating change from June 2015-June 2016 and taking the value of 0 otherwise. Negative rating change (β_3) is a dummy variable equal to 1 in case of negative branch Yelp rating changes, otherwise the dummy takes the value of 0. The remaining category, "No Yelp rating change" is a dummy variable taking the value of 1 if a branch had no Yelp rating change from June 2015-June 2016. It takes the value of 0 otherwise and it is omitted for the regression allowing to analyze the effect of a positive and negative Yelp rating change *in comparison* to having no Yelp rating change.

Table IX reports the corresponding coefficient estimates demonstrating hardly any effect of the rating change variables. Furthermore, all previously discussed results of Table VI remain largely stable, which is particularly important to note for the static Yelp rating variable. As a result, there is no correlation of Yelp rating changes in the year prior to the measurement period of the dependent variable with the latter. At the same time, Table IX affirms the results of the previous part. These results indicate that bank branch deposit volume growth is neither associated with a deterioration nor with an improvement of the Yelp rating. The rating itself, however, continues to exhibit an association with deposit volume growth.

- *Table IX about here: Yelp rating changes and deposit volume growth* -

Despite the fact that the results obtained so far in Tables VIII and IX appear to resemble the baseline in Table VI, they allow for conflicting interpretations. On the one hand, one might speak in favor of an effect of Yelp ratings on branch deposit growth as the long-term Yelp rating seems important as opposed to recent rating changes. On the other hand, the correlations shown might be due to omitted variables speaking against a causal interpretation. Further analysis is therefore required to scrutinize the causal link and in order to shed more light on these interpretations. Subsequently, I rely on a RDD analysis for this purpose.

B. Regression discontinuity analysis

In this section, I test for a causal relationship between Yelp ratings and deposit volume growth. So far, a correlation between these two variables has been found. Despite using fixed effects and lagged variables, causal inference is not yet possible, however. In order to achieve this, I follow Roberts and Sufi (2009) and Anderson and Magruder (2012) in applying a RDD framework. My parametric estimation approach follows Lee and Lemieux

(2010). The core of this methodology is the exploitation of exogenous variation around thresholds. With regard to Yelp, such thresholds are relevant as Yelp ratings are rounded by the system to the nearest 0.5 increment. For example, if the average rating of a bank branch is 2.74, it will be rounded down to 2.5. Only rounded ratings are shown online. Whereas an average rating of 2.76 will be rounded up to 3.0. Consequently, Yelp users will be shown two different ratings with a gap of 0.5 despite the underlying reviews being very similar. I.e., the reason for the difference in rating might be artificial and exogenous due to Yelp's set-up. Provided bank branch deposit volume growth is significantly correlated with such rounding-induced variation, this could be a sign for a causal impact of bank branch Yelp ratings.

An initial graphical RDD analysis is presented in Figure VIII. The graphs show sub-samples by discontinuity threshold and a combined sample (bottom right graph). The x-axis maps the unrounded Yelp rating in June 2016. On the y-axis, annual deposit volume growth from June 2016-June 2017 is depicted. The bandwidth around the rounding thresholds marked by dotted lines is +/- 0.15[17]. If Yelp ratings have a causal effect on deposit volume growth, one would expect growth levels on the right-hand (upward-rounded) side of the thresholds to be *discontinuously* higher than on the left-hand (downward-rounded) side. However, all graphs lead to a similar conclusion: there is hardly any visible difference in deposit volume growth by those branches experiencing a rounding-induced, exogenous treatment "bonus" for their rating.

- Figure VIII about here: Regression discontinuity design (Graphical analysis) -

The multivariate implementation including the measurement of such "rounding treatment" is expressed in equation (4) below.

$$\begin{aligned} Bank\, branch\, deposit\, growth_{i,t,\,2016/2017} = \; & \alpha_t + \beta_1 \times RT_{i,t} + \\ & \beta_2 \times Standardized\, Yelp\, rating_{i,t} + \\ & \beta_3 \times [RT_{i,t} \times Standardized\, Yelp\, rating_{i,t}] + \\ & \varepsilon_{i,t} \end{aligned} \tag{4}$$

In analogy to equation (1), the dependent variable remains the same. Yet, following Lee and Lemieux (2010), I utilize a first-order polynomial for the explanatory variables to grant flexibility, e.g., non-linear functions (cf. Figure VIII), in the function left and right of the threshold. For this reason, β_1 is the estimated effect of the rounding treatment ("RT") of bank branch i when the average of a branch was close to a rounding threshold t on the dependent variable. The standardized Yelp rating$_{\mathrm{i,t}}$ (β_2) is the branch-level Yelp rating obtained by scaling the *unrounded* ratings located at various threshold levels (e.g., 1.75, 2.25 etc.) to a common level. Importantly, the interaction term of $\mathrm{RT}_{\mathrm{i,t}}$ and the

[17]In unreported analysis, I am able to verify that this result is not sensitive to various choices of bandwidths (cf. Anderson and Magruder (2012))

standardized Yelp rating$_{\mathrm{i,t}}$ (β_3) allows "the regression function [to] differ on both sides of the cutoff point" (Lee and Lemieux (2010), p.318). α_t is a threshold fixed effect. The treatment variable $\mathrm{RT}_{\mathrm{i,t}}$ (rounding treatment) is constructed as follows.

$$RT_{i,t} = \begin{cases} 1 & if\, Yelp\, rating_{i,t} \ > rounding\, threshold_t \\ 0 & if\, Yelp\, rating_{i,t} \ < rounding\, threshold_t \end{cases}$$

$\mathrm{RT}_{\mathrm{i,t}}$ is the key explanatory variable taking the value of 1 if a bank branch's Yelp rating is above the rounding threshold a within defined range. The variable takes the value of 0 in case of a rating below a rounding threshold. I.e., $\mathrm{RT}_{\mathrm{i,t}}$=1 would imply that the respective average rating was rounded up whereas another rating with a similar average value, yet just below the threshold, would be rounded down and coded as $\mathrm{RT}_{\mathrm{i,t}}$=0.

Table X reports the results of the RDD analysis. Confirming the graphical analysis, the coefficient for RT is neither statistically nor economically significant (columns 10.1 and 10.2). In addition, some of my control variables to be potentially included in the regression appear to be discontinuous around the thresholds. This implies that treated branches differ from non-treated branches in a discontinuous manner in characteristics other than the rounding treatment. The result is obtained by performing a seemingly unrelated regression (unreported) as suggested by Lee and Lemieux (2010). This approach uses the control variables as dependent variables in individual regressions in order to run a chi-square test as to whether the RT coefficients in all these regressions are jointly equal to zero. The chi-square test returns a significant result rejecting this null hypothesis, however. In another unreported analysis, I also conduct a non-parametric RDD analysis with a triangular kernel function for the estimator obtaining similar results as shown above. As a consequence, a causal effect of Yelp ratings on deposit volume growth is not supported by the RDD results. Potential explanations may be found in the previous discussion about an omitted variables bias implying that factors not captured in my analysis are behind deposit volume growth. Alternatively, the degree of exogenous variation of only 0.5 Yelp rating points might be insufficient to prejudice depositor behavior. Alternatively, insufficient statistical power given the sample size might be a reason.

- Table X about here: Regression discontinuity design (Multivariate analysis) -

V. Conclusion

In this study, I build upon the extant literature centered on the real economy effects of LBSNs and other types of social media networks. The study at hand takes a novel perspective by adding the financial sector in general and branch banking in particular to the debate. Utilizing fixed effects regression analysis, a RDD approach for causal inference and a new dataset from Yelp combined with bank branch data from the FDIC, enables this study to estimate the effect of consumer reviews on deposit volume growth at the branch level. I find that such consumer ratings and their changes are robustly correlated with, yet do not affect the growth of deposits received by bank branches in a causal relation. This is likely due to omitted variables.

With regard to the contribution of the above-mentioned results, I extend prior literature on LBSNs, the literature on the drivers of bank (branch) performance as well as literature on social trading platforms. The findings empirically scrutinize previously-identified mechanisms which have been applied to the financial sector for the first time in the present study. This sector is important as it holds a substantial share of GDP in the United States of almost 10% (BEA (2018b); Greenwood and Scharfstein (2013)). Furthermore, this study shows that depositing and withdrawal behavior of depositors in normal situations at bank branches is not clearly driven by information conveyed in (digital) social networks. This is in contrast with the extreme case of bank runs where it appears to play a role (Kelly and Ó Gráda (2000)). Lastly, the case of Yelp demonstrates that effects of information do not apply to the general depositor public as opposed to the limited set of (professional) investors.

This leads to several implications for the management of retail banks and policymakers alike. Of note here are major banks such as Bank of America and J.P. Morgan Chase Bank, which are preparing for a push into the branch banking market with several hundreds of new branches planned (Henry and Subba (2018)). As such, the presence of these banks in LBSNs as well as an understanding of their mechanics seems to be one part of the factors to consider for this initiative.

On the policy front, the current debate regarding data security, privacy and influencing power of social media companies is likely to result in increased regulation in the near future (Waterson (2018)). Lawmakers might be informed by this study to holistically take into account the real (non-)impact as well as *both* opportunities and caveats surrounding social media including LBSNs. Recent research contributions have argued that the vast amounts of data generated by LBSNs can also be leveraged for the public's benefit (cf. "Nowcasting" in Glaeser et al. (2017), p.4) by enabling governmental institutions to make more data-driven decisions. In addition, economic sentiment may be measured through social media signals as compared to surveys. Since this study provides a perspective on the informativeness of LBSN data, leveraging the exponentially-increasing data volumes should not be confined to the private sector.

References

ABA (2018). Survey: Most popular banking channels. Technical report, American Bankers Association.

AFP (2016). 2016 AFP Electronic Payments Survey. Technical report, Association for Financial Professionals.

Agarwal, S., Chomsisengphet, S., Mahoney, N., and Stroebel, J. (2014). Regulating consumer financial products: Evidence from credit cards. *The Quarterly Journal of Economics*, 130(1):111–164.

Agrawal Sahni, R. and Byrne, T. (2018). Banking regulation 2018 - USA. Technical report, Shearman & Sterling.

Alexa (2018). Alexa traffic ranks - Yelp.com traffic statistics. Technical report, Alexa.

AMA (2015). The internet is gradually replacing traditional media. Technical report, American Marketing Association based on Statista and ZenithOptimedia.

Anderson, M. and Magruder, J. (2012). Learning from the crowd: Regression discontinuity estimates of the effects of an online review database. *The Economic Journal*, 122(563):957–989.

Ashcraft, A. B. et al. (2005). Are banks really special? New evidence from the FDIC-induced failure of healthy banks. *American Economic Review*, 95(5):1712.

Bartov, E., Faurel, L., and Mohanram, P. S. (2017). Can Twitter help predict firm-level earnings and stock returns? *The Accounting Review*, 93(3):25–57.

BEA (2017). International data direct investment & multinational enterprises (MNEs) 2017. Technical report, United States Department of Commerce - Bureau of Economic Analysis.

BEA (2018a). Gross domestic product (GDP) by metropolitan area. Technical report, United States Department of Commerce - Bureau of Economic Analysis.

BEA (2018b). Percentage added to the Gross Domestic Product of the U.S. in 2017. Technical report, United States Department of Commerce - Bureau of Economic Analysis.

Blankespoor, E., Miller, G. S., and White, H. D. (2013). The role of dissemination in market liquidity: Evidence from firms' use of Twitter. *The Accounting Review*, 89(1):79–112.

BLS (2018). Unemployment rate by metropolitan area. Technical report, United States Department of Labor - Bureau of Labor Statistics.

Calomiris, C. W. and Kahn, C. M. (1991). The role of demandable debt in structuring optimal banking arrangements. *The American Economic Review*, 81(3):497–513.

Chari, V. V. and Jagannathan, R. (1988). Banking panics, information, and rational expectations equilibrium. *The Journal of Finance*, 43(3):749–761.

Chen, H., De, P., Hu, Y., and Hwang, B.-H. (2014). Wisdom of crowds: The value of stock opinions transmitted through social media. *The Review of Financial Studies*, 27(5):1367–1403.

Cornett, M. M., Mehran, H., and Tehranian, H. (1998). Are financial markets overly optimistic about the prospects of firms that issue equity? Evidence from voluntary versus involuntary equity issuances by banks. *The Journal of Finance*, 53(6):2139–2159.

Diamond, D. W. and Dybvig, P. H. (1983). Bank runs, deposit insurance, and liquidity. *Journal of Political Economy*, 91(3):401–419.

Drechsler, I., Savov, A., and Schnabl, P. (2018). Banking on Deposits: Maturity Transformation without Interest Rate Risk. National Bureau of Economic Research working paper no. 24582.

FDIC (2017). Deposit market share reports - Summary of deposits. Technical report, Federal Deposit Insurance Corporation.

FDIC (2018a). Number of institutions, branches and total offices FDIC-insured commercial banks U.S. and other areas. Technical report, Federal Deposit Insurance Corporation.

FDIC (2018b). Statistics on depository institutions report - Asset and liabilities. Technical report, Federal Deposit Insurance Corporation.

Glaeser, E. L., Kim, H., and Luca, M. (2017). Nowcasting the local economy: Using Yelp data to measure economic activity. National Bureau of Economic Research working paper no. 24010.

Google Finance (2018). Yelp Inc. stock overview. Technical report, Google.

Greene, C. and Stavins, J. (2018). The 2016 and 2017 surveys of consumer payment choice: summary results. Technical report, Federal Reserve Bank of Boston.

Greenwood, R. and Scharfstein, D. (2013). The growth of finance. *Journal of Economic Perspectives*, 27(2):3–28.

Henry, D. and Subba, N. (2018). BofA to open 500 new U.S. branches in four years. Technical report, Reuters.

IMF (2018). Financial Access Survey (FAS). Technical report, International Monetary Fund.

Iyer, R., Puri, M., and Ryan, N. (2013). Do depositors monitor banks? Technical report, National Bureau of Economic Research.

Iyer, R., Puri, M., and Ryan, N. (2016). A tale of two runs: Depositor responses to bank solvency risk. *The Journal of Finance*, 71(6):2687–2726.

Jayaratne, J. and Strahan, P. E. (1996). The finance-growth nexus: Evidence from bank branch deregulation. *The Quarterly Journal of Economics*, 111(3):639–670.

Jensen, M. C. and Meckling, W. H. (1976). Theory of the firm: Managerial behavior, agency costs and ownership structure. *Journal of Financial Economics*, 3(4):305–360.

Kelly, M. and Ó Gráda, C. (2000). Market contagion: Evidence from the panics of 1854 and 1857. *American Economic Review*, 90(5):1110–1124.

Kiser, E. K. (2002). Predicting household switching behavior and switching costs at depository institutions. *Review of Industrial Organization*, 20(4):349–365.

Lee, D. S. and Lemieux, T. (2010). Regression discontinuity designs in economics. *Journal of Economic Literature*, 48(2):281–355.

Luca, M. (2016). Reviews, reputation, and revenue: The case of Yelp.com. Harvard Business School, Working paper no.12-016.

Luca, M. and Zervas, G. (2016). Fake it till you make it: Reputation, competition, and Yelp review fraud. *Management Science*, 62(12):3412–3427.

Maues, J. (2013). Banking Act of 1933 (Glass-Steagall). Technical report, Federal Reserve Bank of Richmond.

Mayer Brown (2010). Understanding the new financial reform legislation: The Dodd-Frank Wall Street reform and Consumer Protection Act. Technical report, Mayer Brown.

Mayzlin, D., Dover, Y., and Chevalier, J. (2014). Promotional reviews: An empirical investigation of online review manipulation. *American Economic Review*, 104(8):2421–55.

Podium (2017). 2017 state of online reviews - Which online review sites have you visited in the past year to conduct research on a local business? Technical report, Statista.

Roberts, M. R. and Sufi, A. (2009). Control rights and capital structure: An empirical investigation. *The Journal of Finance*, 64(4):1657–1695.

Tolbert, C. and Mossberger, K. (2018). Metro 2013 ACS Microdata. Technical report, Arizona State University. U.S. Current Population Survey & American Community Survey geographic estimates of internet use.

Tranfaglia, A. (2018). Shrinking networks: A spatial analysis of bank branch closures. Technical report, Federal Reserve Bank of Philadelphia.

Turner, A. (2006). *Introduction to neogeography*. O'Reilly Media, Inc.

USCB (2016). 2012-2016 American Community Survey - Median population age by metropolitan area. Technical report, United States Census Bureau.

Waterson, J. (2018). Ofcom to push for regulation of social networks. *The Guardian*.

Yang, D., Zhang, D., Chen, L., and Qu, B. (2014). NationTelescope: Monitoring and visualizing large-scale collective behavior in LBSNs. *Journal of Network and Computer Applications*, 55:170–180.

Yelp Inc. (2018a). Screenshot by the author of a search results screen for a search of the term "bank" in Las Vegas (NV), United States on Yelp.com.

Yelp Inc. (2018b). Screenshot by the author of a typical profile page of a bank in Las Vegas (NV), United States on Yelp.com.

Yelp Inc. (2018c). Screenshot by the author of the list of consumer reviews for a bank in Las Vegas (NV), United States on Yelp.com.

Yelp Inc. (2018d). U.S. demographics of Yelp users. Technical report, Yelp Inc.

Yelp Inc. (2018e). Yelp Inc. form 10-K. Technical report, Yelp Inc.

Yelp Inc. (2018f). Yelp investor relations letter to shareholders. Technical report, Yelp Inc.

Tables

Table I: Socioeconomic characteristics of geographies covered

The table shows social and economic characteristics of the metropolitan areas covered by the Yelp data. Figures are for 2017 with the exception of unemployment rate (2018), age (2016) and internet usage (2017) due to availability. A metropolitan area includes the agglomeration around the core cities mentioned in the table. Data sources: BEA (2017) for GDP, BLS (2018) for unemployment, USCB (2016) for population and age figures, and Tolbert and Mossberger (2018) for internet use.

	Gross domestic product						Internet use	
Metropolitan area (State)	Level (USD mio.)	Per capita (USD)	Growth '16-'17 (%)	Unemployment (%)	Population (Inhabitants)	Median inhab. age (Years)	Broadband (%)	Mobile (%)
Charlotte (NC)	174,029	68,914	3.5	2.9	2,525,305	33.8	75.6	34.3
Cleveland (OH)	138,980	67,503	2.9	4.4	2,058,844	35.8	75.3	32.9
Columbus (OH)	136,296	65,567	2.1	3.6	2,078,725	32.1	78.9	39.1
Las Vegas (NV)	112,288	50,945	2.7	4.7	2,204,079	37.4	77.9	36.6
Madison (WI)	49,853	82,342	1.8	2.0	605,435	30.8	76.2	38.7
Philadelphia (PA)	444,975	72,993	1.4	4.1	6,096,120	33.9	78.0	34.8
Phoenix (AZ)	242,951	51,285	3.4	4.2	4,737,270	33.3	76.5	33.1
Pittsburgh (PA)	147,367	63,156	3.7	3.7	2,333,367	32.9	75.4	31.6
Urbana-Champaign (IL)	12,177	52,511	0.2	3.8	231,891	24.0	74.1	30.8
Average	162,101	63,913	2.4	3.7	2,541,226	32.7	76.4	34.7
Median	138,980	65,567	2.7	3.8	2,204,079	33.3	76.2	34.3
U.S. metropolitan areas - Average	45,817	49,460	1.6	3.6	730,979	37.7	73.6	33.7

Table II: Summary statistics - Characteristics of bank branches and their Yelp reviews

The sample includes 683 Yelp-rated bank branches (June 2016). Approximately 33% of all bank branches in the cities covered by the Yelp data are rated on Yelp and so are 25% of all branches in the counties covered. Covered cities include 1,949 bank branches in total including Yelp-rated branches. Covered counties include 2,745 branches in total including Yelp-rated branches. Figures under "Branches without Yelp rating (City)/ (County)" refer to all FDIC-registered bank branches in cities/ counties covered by the Yelp data and exclude Yelp-rated branches. The bank branch Yelp "star" rating is measured from 1 (worst rating) to 5 (best rating) in 0.5 increments. The rating is calculated as the average of all ratings received rounded to the nearest increment. Years of operation and branch location data is obtained from the FDIC "Summary of Deposits" files. Statistical significance levels and t-values for the difference between branches in different rating level categories are obtained by two-sample t-tests. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

							Percentiles					
Variable	Unit	N	Mean	SD	Min	Max	5th	25th	50th	75th	95th	Difference (rating level)
Number of branches with Yelp rating per bank	Branches	683	10.34	33.48	1	164	1	1	1	3	58	
Number of locations per bank	Cities	683	2.93	5,260	1	26	1	1	1	2	15	
Yelp rating	Stars	683	2.863	1.085	1	5	1	2	3	3.5	5	
Number of user reviews												
Branches with Yelp rating	Reviews	3,204	4.391	3.100	1	19	1	2	3	5	11	
Branches with Yelp rating 1 - 1.5	Reviews	490	3.467	2.748	1	18	1	2	3	4	8	
Branches with Yelp rating 2 - 2.5	Reviews	1,192	5.347	3.467	1	19	2	3	4	6	13	
Branches with Yelp rating 3 - 3.5	Reviews	1,054	4.643	3.038	1	19	2	3	4	6	11	
Branches with Yelp rating 4 - 5	Reviews	468	3.319	2.303	1	13	1	2	3	4	8	
Branches with Yelp rating 1 - 3.5	Reviews	2,736	4.674	3.221	1	19	1	3	4	6	12	
Branches with Yelp rating 4 - 5	Reviews	468	3.319	2.303	1	13	1	2	3	4	8	4.69***
Years of operation of branches												
Branches without Yelp rating (County)	Years	2,062	38.48	34.26	2	117	5	12	24	55	117	
Branches without Yelp rating (City)	Years	1,266	33.28	32.48	2	117	5	10	19	46	117	
Branches with Yelp rating	Years	683	28.32	25.08	4	117	7	11	18	37	82	

Table III: Summary statistics - Characteristics of Yelp reviewers

The sample includes 683 Yelp-rated bank branches (June 2016) and 3,204 reviews by 2,675 reviewers. The number of Yelp "Elite" reviewers is defined as the number of all Yelp reviewers with “Elite squad” status in 2016 and/ or 2015 who have rated a bank branch (badge icon shown on the user profile; obtained as a reward scheme for, e.g., regular review activity, photo uploads etc.). The average reviewer number of "useful" review tags stands for the average number of “useful” Yelp rating tags (tags can be given by other users) received by all reviewers of a bank branch. The average reviewer Yelp tenure is the average time all reviewers of a bank branch have been registered on Yelp measured in years. The average reviewer number of Yelp reviews is the average number of Yelp total reviews of all reviewers of a bank branch. The average reviewer Yelp rating is the average Yelp rating by all reviewers of a bank branch measured in Yelp rating “stars”. The number of negative attitude reviewers is defined as the number of reviewers of a bank branch who a) have, overall, assigned average Yelp ratings of below and equal to 2.5 and b) have assigned average Yelp ratings of below and equal to 2.5 to bank branches. The bank branch Yelp rating is measured from 1 (worst rating) to 5 (best rating) in 0.5 increments. The rating is calculated as the average of all ratings received rounded to the nearest increment.

							Percentiles				
Variable	Unit	N	Mean	SD	Min	Max	5th	25th	50th	75th	95th
Number of Yelp "Elite" reviewers	Number	683	0.735	0.966	0	6	0	0	0	1	3
Average reviewer number of "useful" review tags	Number	683	523.00	1,468	0	11,514	1	15.500	74.668	299.472	2,302
Average reviewer Yelp tenure	Years	683	4.067	1.278	0.785	7.337	1.968	3.230	3.982	4.921	6.344
Average reviewer number of Yelp reviews	Number	683	184.761	208.3	4	1,459	12	42.67	112	254.6	602
Average reviewer Yelp rating	Stars	683	3.479	0.488	1.270	4.530	2.617	3.210	3.514	3.805	4.205
Number of negative attitude reviewers	Number	683	0.091	0.330	0	3	0	0	0	0	1
Reviews included in analysis	Number	3,204									
Reviewers included in analysis	Number	2,675									

Table IV: Summary statistics - Characteristics of bank branch deposit volume

The sample includes 683 Yelp-rated bank branches (June 2016). Approximately 33% of all bank branches in the cities covered by the Yelp data are rated on Yelp and so are 25% of all branches in the counties covered. Covered cities include 1,949 bank branches in total including Yelp-rated branches. Covered counties include 2,745 branches in total including Yelp-rated branches. Figures under "Branches without Yelp rating (City)/ (County)" refer to all FDIC-registered bank branches in cities/ counties covered by the Yelp data and exclude Yelp-rated branches. Deposit volume (in USD thousands) and branch location data is obtained from the FDIC "Summary of Deposits" files. Statistical significance levels and t-values for the difference between branches in different rating level categories are obtained by two-sample t-tests. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

							Percentiles					
Variable	Unit	N	Mean	SD	Min	Max	5th	25th	50th	75th	95th	Difference (rating level)
Branches without Yelp rating (County)	USD '000	2,062	68,836	96,882	1,281	1,132,000	6,324	23,093	44,114	78,132	194,063	
Branches without Yelp rating (City)	USD '000	1,266	73,411	114,489	1,281	1,132,000	5,099	20,478	40,291	79,369	230,911	
Branches with Yelp rating	USD '000	683	110,614	202,672	4,187	4,030,000	15,638	42,839	74,312	129,077	249,314	
Branches with Yelp rating 1 - 1.5	USD '000	108	99,661	117,766	5,715	915,600	13,024	42,839	67,683	116,485	267,374	
Branches with Yelp rating 2 - 2.5	USD '000	207	128,515	304,664	12,312	4,030,000	24,278	48,331	82,483	140,109	246,655	
Branches with Yelp rating 3 - 3.5	USD '000	227	106,504	129,498	4,187	1,133,000	13,753	43,715	74,972	129,808	240,038	
Branches with Yelp rating 4 - 5	USD '000	141	99,734	162,286	6,050	1,792,000	12,865	35,377	69,801	111,011	244,456	
Branches with Yelp rating 1 - 3.5	USD '000	542	113,482	212,084	4,187	4,030,000	17,927	44,387	74,982	130,248	249,314	
Branches with Yelp rating 4 - 5	USD '000	141	99,734	162,286	6,050	1,792,000	12,865	35,377	69,801	111,011	244,456	0.71

Table V: Summary statistics - Characteristics of bank branch deposit volume growth

The sample includes 683 Yelp-rated bank branches (June 2016). Approximately 33% of all bank branches in the cities covered by the Yelp data are rated on Yelp and so are 25% of all branches in the counties covered. Covered cities include 1,949 bank branches in total including Yelp-rated branches. Covered counties include 2,745 branches in total including Yelp-rated branches. Figures under "Branches without Yelp rating (City)/ (County)" refer to all FDIC-registered bank branches in cities/ counties covered by the Yelp data and exclude Yelp-rated branches. Deposit volume growth is calculated as the change in percentage decimals (1% = 0.01) in deposit volumes from June 2016-June 2017 of each branch in the sample (branch location data is obtained from the FDIC "Summary of Deposits" files). Statistical significance levels and t-values for the difference between branches in different rating level categories are obtained by two-sample t-tests. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

							Percentiles					
Variable	Unit	N	Mean	SD	Min	Max	5th	25th	50th	75th	95th	Difference (rating level)
Branches without Yelp rating (County)	USD '000	2,062	4,293	12,944	-62,005	110,729	-7,177	74	2,286	6,042	20,721	
Branches without Yelp rating (County)	%	2,062	0.0969	0.196	-0.408	1.326	-0.131	0.00352	0.0648	0.145	0.408	
Branches without Yelp rating (City)	USD '000	1,266	4,809	14,736	-62,005	110,729	-8,424	128	2,398	6,272	24,021	
Branches without Yelp rating (City)	%	1,266	0.110	0.215	-0.408	1.326	-0.138	0.00708	0.0730	0.157	0.454	
Branches with Yelp rating	USD '000	683	10,106	18,249	-57,877	205,510	-3,150	2,950	6,508	13,334	33,205	
Branches with Yelp rating	%	683	0.122	0.138	-0.155	0.993	-0.0462	0.0528	0.0990	0.166	0.337	
Branches with Yelp rating 1 - 1.5	%	108	0.0993	0.0953	-0.114	0.450	-0.0515	0.0483	0.0839	0.152	0.253	
Branches with Yelp rating 2 - 2.5	%	207	0.115	0.117	-0.145	0.993	-0.0197	0.0601	0.101	0.151	0.289	
Branches with Yelp rating 3 - 3.5	%	227	0.122	0.131	-0.155	0.890	-0.0606	0.0530	0.101	0.176	0.343	
Branches with Yelp rating 4 - 5	%	141	0.152	0.192	-0.141	0.887	-0.0384	0.0459	0.0966	0.196	0.528	
Branches with Yelp rating 1 - 3.5	%	542	0.115	0.119	-0.155	0.993	-0.0484	0.0541	0.0991	0.161	0.306	
Branches with Yelp rating 4 - 5	%	141	0.152	0.192	-0.141	0.887	-0.0384	0.0459	0.0966	0.196	0.528	2.85***

Table VI: Yelp ratings and bank branch deposit volume growth

The table shows coefficient estimates and standard errors of fixed-effects OLS regression models. The sample for all specifications includes all 683 Yelp-rated branches in June 2016. The dependent variable is the bank branch deposit volume growth rate from June 2016-June 2017 measured in percentage decimals (1% = 0.01). The growth rate is calculated as the change in deposit volumes from June 2016-June 2017 of each branch in the sample. The bank branch Yelp rating is measured from 1 (worst rating) to 5 (best rating) in 0.5 increments. The rating is calculated as the average of all ratings received rounded to the nearest increment. Bank branch deposit volume is the volume of deposits held, measured in USD. Bank branch years of operation is the time a bank branch has been operating since establishment measured in years. The number of branch Yelp reviews expresses the total number of Yelp reviews received. Review and reviewer controls include: the number of Yelp "Elite" reviewers defined as the number of all Yelp reviewers with “Elite squad” status in 2016 and/ or 2015 who have rated a bank branch (badge icon shown on the user profile; obtained as a reward scheme for, e.g., regular review activity, photo uploads etc.); the average reviewer number of "useful" review tags standing for the average number of “useful” Yelp rating tags (tags can be given by other users) received by all reviewers of a bank branch; the average reviewer Yelp tenure defined as the average time all reviewers of a bank branch have been registered on Yelp measured in years; the average reviewer number of Yelp reviews defined as the average number of Yelp total reviews of all reviewers of a bank branch; the average reviewer Yelp rating is the average Yelp rating by all reviewers of a bank branch measured in Yelp rating “stars” and the number of negative attitude reviewers is defined as the number of reviewers of a bank branch who a) have, overall, assigned average Yelp ratings of below and equal to 2.5 and b) have assigned average Yelp ratings of below and equal to 2.5 to bank branches. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	All Yelp-rated branches											
	(6.1)	(6.2)	(6.3)	(6.4)	(6.5)	(6.6)	(6.7)	(6.8)	(6.9)	(6.10)	(6.11)	(6.12)
Bank branch Yelp rating	0.010**	0.010**	0.013***	0.011**	0.013***	0.011**	0.012**	0.012*	0.014**	0.014**	0.014**	0.014**
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Bank branch deposit volume	-0.000**	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Number of branch Yelp reviews	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002	-0.004*	-0.004*	-0.004*	-0.004*	-0.004*	-0.004*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Bank branch years of operation		-0.001**		-0.001***		-0.001***	-0.000*	-0.000	-0.001***	-0.001***	-0.001***	-0.001**
		(0.000)		(0.000)		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.074	0.081	-0.001	0.047	0.093***	0.115***	0.077	0.072	0.043	0.040	0.130***	0.126***
	(0.125)	(0.124)	(0.034)	(0.037)	(0.018)	(0.019)	(0.132)	(0.133)	(0.053)	(0.053)	(0.044)	(0.045)
Review & reviewer controls	-	-	-	-	-	-	Yes	Yes	Yes	Yes	Yes	Yes
Bank F.E.	Yes	Yes	-	-	-	-	Yes	Yes	-	-	-	-
County F.E.	-	-	Yes	Yes	-	-	-	-	Yes	Yes	-	-
State F.E.	-	-	-	-	Yes	Yes	-	-	-	-	Yes	Yes
Mean of dependent variable	0.122	0.122	0.122	0.122	0.122	0.122	0.122	0.122	0.122	0.122	0.122	0.122
Observations	654	654	654	654	654	654	622	622	622	622	622	622
R-squared	0.282	0.287	0.069	0.082	0.054	0.067	0.285	0.285	0.091	0.092	0.076	0.076
Adjusted R-squared	0.200	0.204	0.048	0.061	0.041	0.052	0.194	0.193	0.061	0.061	0.053	0.052

Table VII: Yelp ratings and bank branch deposit volume growth - Robustness test

The table shows coefficient estimates and standard errors of fixed-effects OLS regression models. The sample in columns 7.1-7.6 excludes lowest-rated branches with a Yelp rating of 1 in June 2016. The sample in columns 7.7-7.12 excludes highest-rated branches with a Yelp rating of 5 in June 2016. The dependent variable is the bank branch deposit volume growth rate from June 2016-June 2017 measured in percentage decimals (1% = 0.01). The growth rate is calculated as the change in deposit volumes from June 2016-June 2017 of each branch in the sample. The bank branch Yelp rating is measured from 1 (worst rating) to 5 (best rating) in 0.5 increments. The rating is calculated as the average of all ratings received rounded to the nearest increment. Bank branch deposit volume is the volume of deposits held, measured in USD. Bank branch years of operation is the time a bank branch has been operating since establishment measured in years. The number of branch Yelp reviews expresses the total number of Yelp reviews received. Review and reviewer controls include: the number of Yelp "Elite" reviewers defined as the number of all Yelp reviewers with “Elite squad” status in 2016 and/ or 2015 who have rated a bank branch (badge icon shown on the user profile; obtained as a reward scheme for, e.g., regular review activity, photo uploads etc.); the average reviewer number of "useful" review tags standing for the average number of “useful” Yelp rating tags (tags can be given by other users) received by all reviewers of a bank branch; the average reviewer Yelp tenure defined as the average time all reviewers of a bank branch have been registered on Yelp measured in years; the average reviewer number of Yelp reviews defined as the average number of Yelp total reviews of all reviewers of a bank branch; the average reviewer Yelp rating is the average Yelp rating by all reviewers of a bank branch measured in Yelp rating “stars” and the number of negative attitude reviewers is defined as the number of reviewers of a bank branch who a) have, overall, assigned average Yelp ratings of below and equal to 2.5 and b) have assigned average Yelp ratings of below and equal to 2.5 to bank branches. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Excluding lowest-rated branches						Excluding highest-rated branches					
	(7.1)	(7.2)	(7.3)	(7.4)	(7.5)	(7.6)	(7.7)	(7.8)	(7.9)	(7.10)	(7.11)	(7.12)
Bank branch Yelp rating	0.011*	0.013**	0.013**	0.013*	0.015**	0.015**	0.011**	0.017***	0.017***	0.012*	0.018***	0.018***
	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)
Bank branch deposit volume	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Number of branch Yelp reviews	-0.002	-0.001	-0.001	-0.004*	-0.004	-0.004	-0.002	-0.002	-0.002	-0.004*	-0.004*	-0.004*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Bank branch years of operation	-0.000*	-0.001***	-0.001**	-0.000	-0.001***	-0.001***	-0.001**	-0.001***	-0.001***	-0.000*	-0.001***	-0.001**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.076	0.037	0.106***	0.056	0.036	0.122**	0.076	0.030	0.106***	0.076	0.023	0.118***
	(0.128)	(0.042)	(0.025)	(0.140)	(0.063)	(0.056)	(0.117)	(0.036)	(0.019)	(0.125)	(0.051)	(0.044)
Review & reviewer controls	-	-	-	-	-	-	Yes	Yes	Yes	Yes	Yes	Yes
Bank F.E.	Yes	-	-	Yes	-	-	Yes	-	-	Yes	-	-
County F.E.	-	Yes	-	-	Yes	-	-	Yes	-	-	Yes	-
State F.E.	-	-	Yes	-	-	Yes	-	-	Yes	-	-	Yes
Mean of dependent variable	0.124	0.124	0.124	0.124	0.124	0.124	0.122	0.122	0.122	0.122	0.122	0.122
Observations	597	597	597	573	573	573	610	610	610	584	584	584
R-squared	0.282	0.085	0.070	0.284	0.100	0.084	0.327	0.115	0.083	0.320	0.123	0.090
Adjusted R-squared	0.195	0.062	0.054	0.188	0.066	0.058	0.247	0.093	0.068	0.230	0.091	0.065

Table VIII: Yelp rating category and bank branch deposit volume growth

The table shows coefficient estimates and standard errors of fixed-effects OLS regression models. The full sample includes 2,745 FDIC-registered branches in June 2016, both Yelp-rated and non-rated which are located in the counties covered by the Yelp data. This full sample is filtered for those banks (counties and states) entailing branches in all three rating categories in order to apply bank (county and state) fixed effects in the respective subsamples. The dependent variable is the bank branch deposit volume growth rate from 2016-2017 measured in percentage decimals (1% = 0.01). The growth rate is calculated as the change in deposit volumes from June 2016-June 2017 of each branch in the sample. High rating category is a dummy variable taking the value of 1 if a branch has a high Yelp rating of 4, 4.5 or 5 and taking the value of 0 otherwise. Low rating category is a dummy variable equal to 1 in case of low branch Yelp ratings 1-3.5, otherwise the dummy takes the value of 0. The omitted category is "No Yelp rating" which is a dummy variable taking the value of 1 if a branch had no Yelp rating in June 2016 and taking the value of 0 otherwise. Bank branch deposit volume is the volume of deposits held, measured in USD. Bank branch years of operation is the time a bank branch has been operating since establishment measured in years. The number of branch Yelp reviews expresses the total number of Yelp reviews received. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	All Yelp-rated branches (omitted category: no Yelp rating)					
	(8.1)	(8.2)	(8.3)	(8.4)	(8.5)	(8.6)
High rating category	-0.081	-0.079	0.049***	0.049***	0.047**	0.048***
	(0.053)	(0.052)	(0.019)	(0.019)	(0.019)	(0.018)
Low rating category	-0.108**	-0.103**	0.017	0.023	0.015	0.020
	(0.052)	(0.051)	(0.016)	(0.015)	(0.016)	(0.015)
Bank branch deposit volume	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Number of branch Yelp reviews	-0.002	-0.002	-0.003	-0.003	-0.003	-0.003
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Bank branch years of operation		-0.001***		-0.001***		-0.001***
		(0.000)		(0.000)		(0.000)
Constant	0.212	0.217	0.056***	0.102***	0.136***	0.152***
	(0.178)	(0.176)	(0.009)	(0.011)	(0.008)	(0.008)
Bank F.E.	Yes	Yes	-	-	-	-
County F.E.	-	-	Yes	Yes	-	-
State F.E.	-	-	-	-	Yes	Yes
Mean of dependent variable	0.118	0.118	0.105	0.105	0.103	0.103
Observations	1,450	1,450	2,381	2,381	2,608	2,608
R-squared	0.143	0.170	0.037	0.063	0.041	0.064
Adjusted R-squared	0.117	0.144	0.034	0.059	0.036	0.059

Table IX: Yelp rating changes and bank branch deposit volume growth

The table shows coefficient estimates and standard errors of fixed-effects OLS regression models. The sample for all columns includes all 683 Yelp-rated branches in June 2016. The dependent variable is the bank branch deposit volume growth rate from June 2016-June 2017 measured in percentage decimals (1% = 0.01). The growth rate is calculated as the change in deposit volumes from June 2016-June 2017 of each branch in the sample. Positive (Negative) Yelp rating change (2015-2016) is a dummy variable taking the value of 1 if the Yelp rating of a branch is higher (lower) in June 2016 compared to June 2015. The omitted category is "No Yelp rating change" which is a dummy variable taking the value of 1 of a the Yelp rating of a branch did not change and 0 otherwise. The bank branch Yelp rating is measured from 1 (worst rating) to 5 (best rating) in 0.5 increments. The rating is calculated as the average of all ratings received rounded to the nearest increment. Bank branch deposit volume is the volume of deposits held, measured in USD. Bank branch years of operation is the time a bank branch has been operating since establishment measured in years whereas the number of branch Yelp reviews expresses the total number of Yelp reviews received. Review and reviewer controls include: the number of Yelp "Elite" reviewers defined as the number of all Yelp reviewers with "Elite squad" status in 2016 and/ or 2015 who have rated a bank branch (badge icon shown on the user profile; obtained as a reward scheme for, e.g., regular review activity, photo uploads etc.); the average reviewer number of "useful" review tags standing for the average number of "useful" Yelp rating tags (tags can be given by other users) received by all reviewers of a bank branch; the average reviewer Yelp tenure defined as the average time all reviewers of a bank branch have been registered on Yelp measured in years; the average reviewer number of Yelp reviews defined as the average number of Yelp total reviews of all reviewers of a bank branch; the average reviewer Yelp rating is the average Yelp rating by all reviewers of a bank branch measured in Yelp rating "stars" and the number of negative attitude reviewers is defined as the number of reviewers of a bank branch who a) have, overall, assigned average Yelp ratings of below and equal to 2.5 and b) have assigned average Yelp ratings of below and equal to 2.5 to bank branches. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Yelp-rated branches (omitted category: no rating change 2015-2016)											
	(9.1)	(9.2)	(9.3)	(9.4)	(9.5)	(9.6)	(9.7)	(9.8)	(9.9)	(9.10)	(9.11)	(9.12)
Positive Yelp rating change (2015-2016)	-0.028*	-0.028*	0.015	0.015	-0.010	-0.010	-0.025	-0.024	-0.015	-0.014	-0.015	-0.015
	(0.015)	(0.015)	(0.013)	(0.012)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
Negative Yelp rating change (2015-2016)	0.004	0.004	-0.012	-0.010	0.015	0.016	0.005	0.005	0.009	0.009	0.010	0.010
	(0.012)	(0.012)	(0.016)	(0.015)	(0.012)	(0.012)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Bank branch Yelp rating	0.012**	0.012**	0.014***	0.012**	0.012**	0.012**	0.014*	0.013*	0.014**	0.014**	0.014**	0.014**
	(0.006)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Bank branch deposit volume	-0.000***	-0.000***	-0.000	-0.000	-0.000	-0.000	-0.000**	-0.000**	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Number of branch Yelp reviews	-0.001	-0.002	-0.001	-0.001	-0.001	-0.001	-0.004	-0.004*	-0.004*	-0.004*	-0.004*	-0.004*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Bank branch years of operation		-0.000		-0.001***		-0.001***	-0.000	-0.000	-0.001***	-0.001***	-0.001***	-0.001***
		(0.000)		(0.000)		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.074	0.079	0.003	0.063	0.108***	0.113***	0.071	0.063	0.064	0.058	0.123**	0.117**
	(0.125)	(0.125)	(0.036)	(0.039)	(0.020)	(0.021)	(0.135)	(0.135)	(0.057)	(0.058)	(0.049)	(0.050)
Review & reviewer controls	-	-	-	-	-	-	Yes	Yes	Yes	Yes	Yes	Yes
Bank F.E.	Yes	Yes	-	-	-	-	Yes	Yes	-	-	-	-
County F.E.	-	-	Yes	Yes	-	-	-	-	Yes	Yes	-	-
State F.E.	-	-	-	-	Yes	Yes	-	-	-	-	Yes	Yes
Mean of dependent variable	0.101	0.101	0.101	0.101	0.101	0.101	0.101	0.101	0.101	0.101	0.101	0.101
Observations	586	586	586	586	586	586	563	563	563	563	563	563
R-squared	0.268	0.271	0.073	0.094	0.075	0.076	0.264	0.266	0.099	0.100	0.080	0.081
Adjusted R-squared	0.176	0.178	0.047	0.067	0.058	0.057	0.163	0.163	0.062	0.061	0.051	0.051

Table X: Regression discontinuity analysis (Yelp ratings and bank branch deposit volume growth)

The table shows coefficient estimates and standard errors of a parametric, first-order polynomial RDD. The sample for all columns includes those 297 Yelp-rated branches within a +/- 0.15 bandwidth around discontinuity rounding thresholds in June 2016. The dependent variable is the bank branch deposit volume growth rate from June 2016-June 2017 measured in percentage decimals (1% = 0.01). The growth rate is calculated as the change in deposit volumes from June 2016-June 2017 of each branch in the sample. Rounding treatment (RT) is a discontinuity dummy variable equal to 1 if the *unrounded* average Yelp rating of a branch in June 2016 is above the rounding threshold and 0 otherwise. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Bandwidth: +/- 0.15	
	(10.1)	(10.2)
Rounding treatment (RT)	0.000	0.005
	(0.028)	(0.030)
Rounding threshold F.E.	-	Yes
Model	Parametric, first-order polynomial	Parametric, first-order polynomial
Observations	297	297
R-squared	0.021	0.050
Adjusted R-squared	0.011	0.017

Figures

Figure I: Distribution of deposit volume growth of bank branches in the U.S.

The figure shows the frequency distribution of deposit volume growth of 87,031 bank branches in the United States for which FDIC deposit volume data is available. Deposit volume growth is calculated as the change in percentage decimals (1% = 0.01) in deposit volumes from June 2016-June 2017 of each branch in the sample.

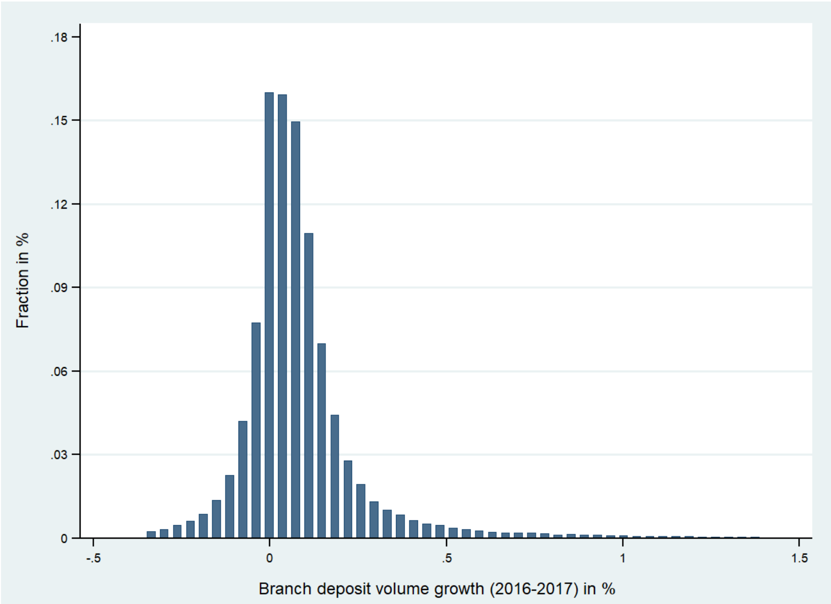


Figure II: Sample illustration of a Yelp search results page

The figure shows the search results screen on Yelp.com for a search of the term “bank” in Las Vegas (NV), United States (Yelp Inc. (2018a)). Besides the overall Yelp “star” rating (from 1 to 5 in half increments), the number of reviews, the address and the map location of rated bank branches are provided.

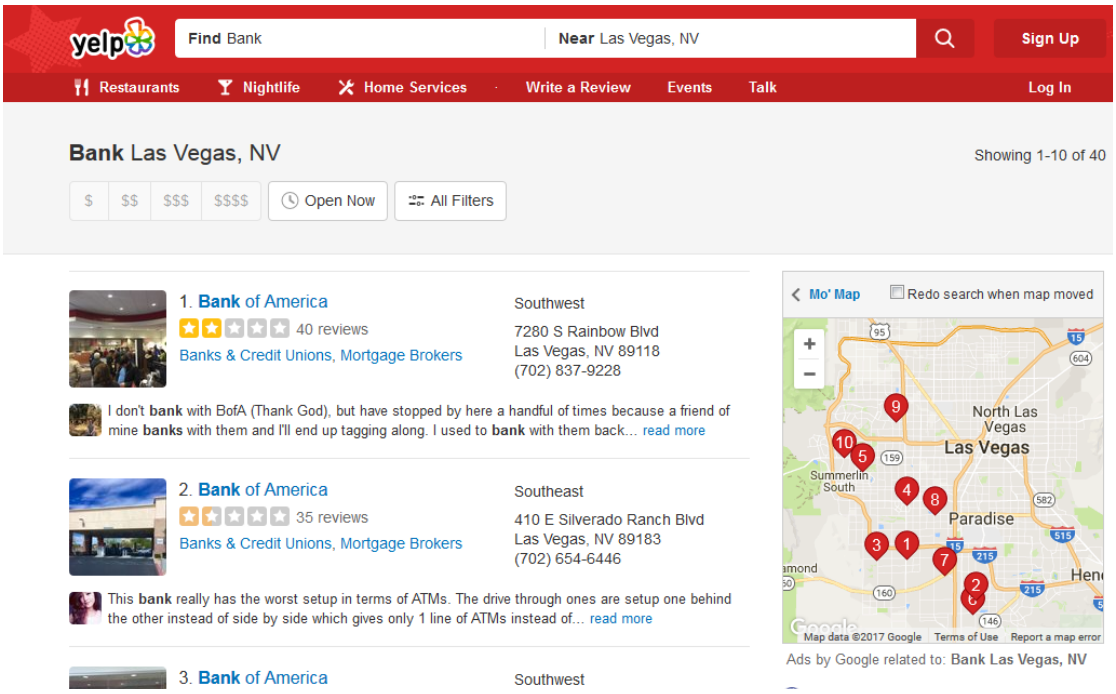


Figure III: Sample illustration of a Yelp business profile

The figure shows a typical profile page of a bank in Las Vegas (NV), United States on Yelp.com (Yelp Inc. (2018b)). Besides the overall Yelp rating (from 1 to 5 in half increments), the number of reviews, the address, the map location and photos of the rated branch are provided. The detailed consumer reviews are attached below each business profile (see also Figure IV).

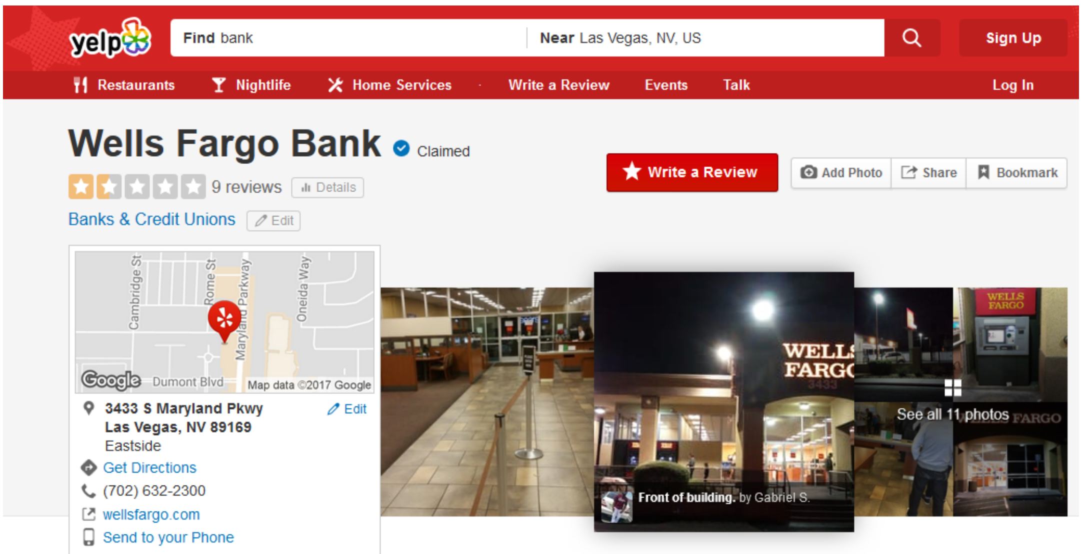
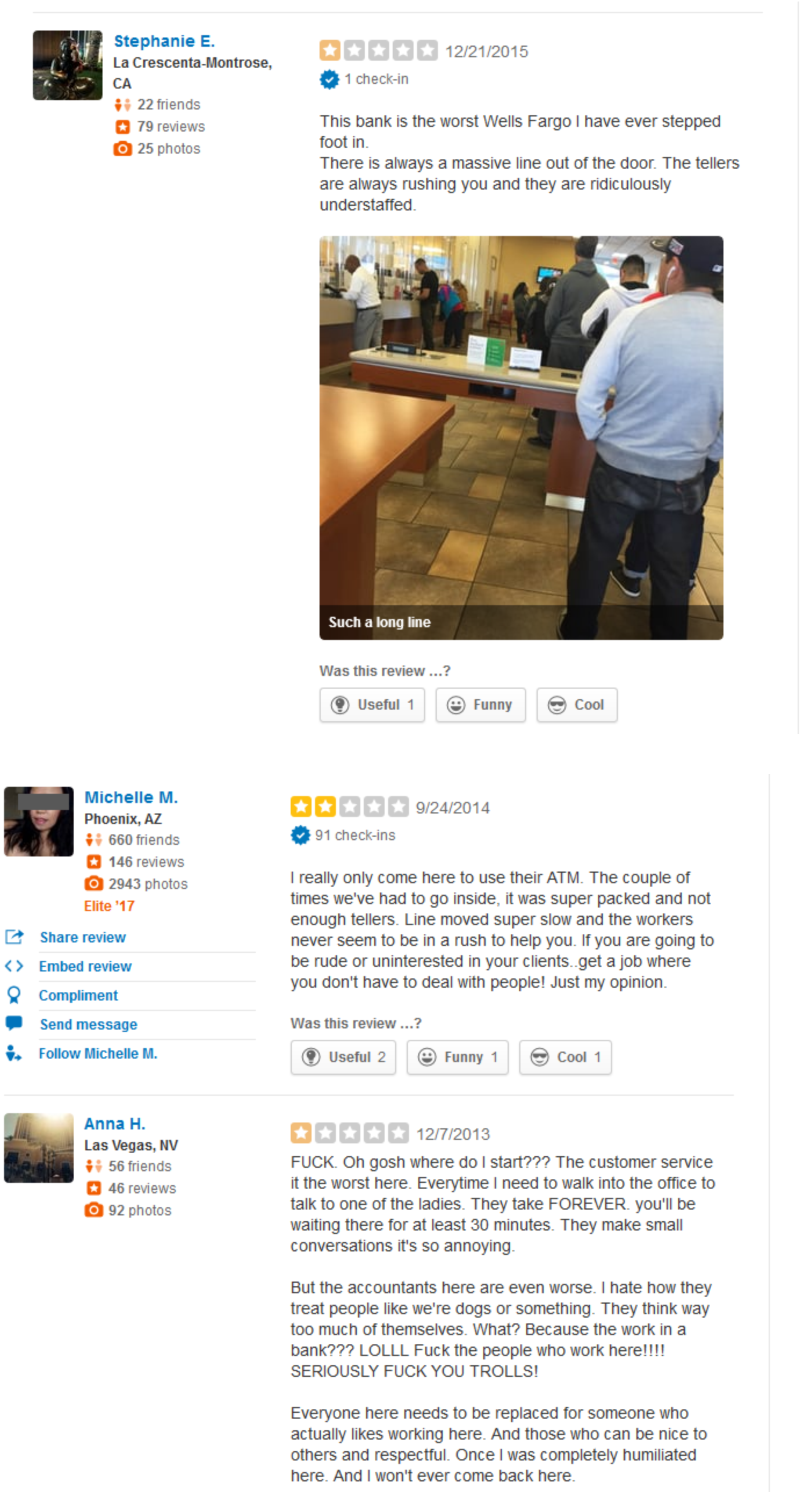


Figure IV: Sample illustration of consumer reviews on a Yelp business profile

The figure shows an excerpt of the list of consumer reviews for a bank in Las Vegas (NV), United States on Yelp.com (Yelp Inc. (2018c)). Each review is comprised of the Yelp rating and its date, user profile and statistics as well as a comment and photos.



Stephanie E.
La Crescenta-Montrose, CA
22 friends
79 reviews
25 photos

12/21/2015
1 check-in

This bank is the worst Wells Fargo I have ever stepped foot in.
There is always a massive line out of the door. The tellers are always rushing you and they are ridiculously understaffed.

Such a long line

Was this review ...?
Useful 1 | Funny | Cool

Michelle M.
Phoenix, AZ
660 friends
146 reviews
2943 photos
Elite '17

Share review
Embed review
Compliment
Send message
Follow Michelle M.

9/24/2014
91 check-ins

I really only come here to use their ATM. The couple of times we've had to go inside, it was super packed and not enough tellers. Line moved super slow and the workers never seem to be in a rush to help you. If you are going to be rude or uninterested in your clients..get a job where you don't have to deal with people! Just my opinion.

Was this review ...?
Useful 2 | Funny 1 | Cool 1

Anna H.
Las Vegas, NV
56 friends
46 reviews
92 photos

12/7/2013

FUCK. Oh gosh where do I start??? The customer service it the worst here. Everytime I need to walk into the office to talk to one of the ladies. They take FOREVER. you'll be waiting there for at least 30 minutes. They make small conversations it's so annoying.

But the accountants here are even worse. I hate how they treat people like we're dogs or something. They think way too much of themselves. What? Because the work in a bank??? LOLLL Fuck the people who work here!!!! SERIOUSLY FUCK YOU TROLLS!

Everyone here needs to be replaced for someone who actually likes working here. And those who can be nice to others and respectful. Once I was completely humiliated here. And I won't ever come back here.

Figure V: Geographic coverage of the Yelp dataset

The figure shows the geographical spread and population figures of the geographies covered by the Yelp data (own illustration based on USCB (2016) data). The following metropolitan areas are included (in alphabetical order): Charlotte (NC), Cleveland (OH), Columbus (OH), Las Vegas (NV), Madison (WI), Philadelphia (PA), Phoenix (AZ), Pittsburgh (PA) and Urbana-Champaign (IL). Coverage extends to most cities located in the respective counties but not to all of them.

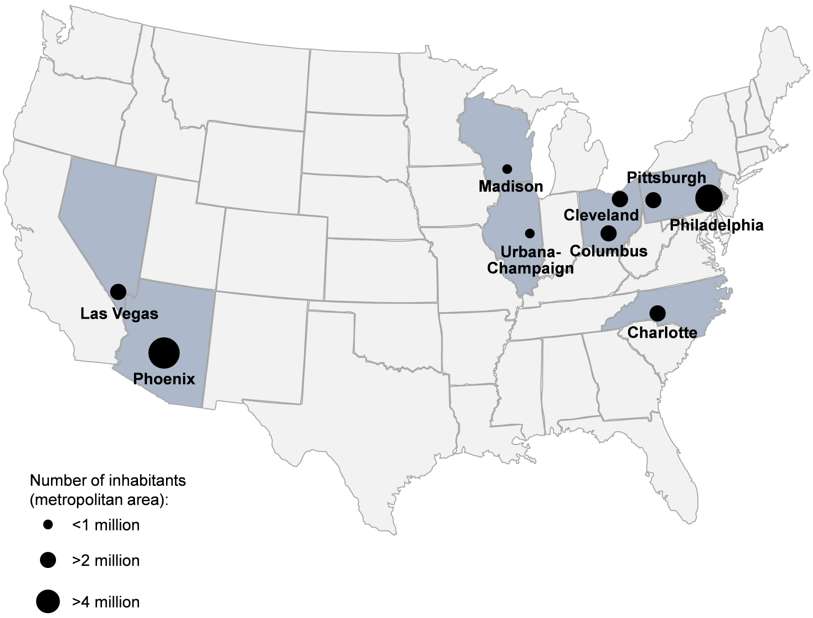


Figure VI: Number of Yelp consumer reviews by Yelp rating category

The figure shows the average number of Yelp consumer reviews bank branches have received (blue bars) by Yelp rating category in June 2016. Number of branches by rating category: 108 for 1-1.5, 207 for 2-2.5, 227 for 3-3.5 and 141 for 4-5. The average figure for the total sample combining all ratings categories (683 branches) is also included (dashed line).

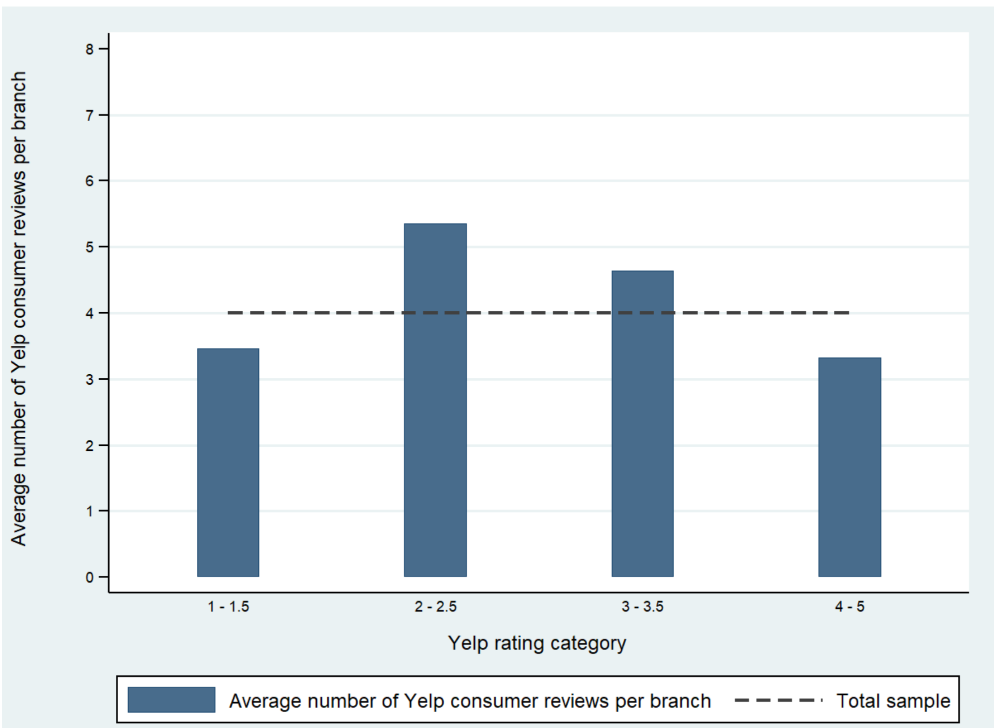


Figure VII: Bank branch deposit volume growth by Yelp rating category

The figure shows the average bank branch deposit volume growth (blue bars) by Yelp rating category from June 2016-June 2017. Deposit volume growth has been calculated as the change in percentage decimals (1% = 0.01) in deposit volumes from June 2016-June 2017 of each branch in the sample. Number of branches by rating category: 108 for 1-1.5, 207 for 2-2.5, 227 for 3-3.5 and 141 for 4-5. The average figure for the total sample combining all ratings categories (683 branches) is also included (dashed line).

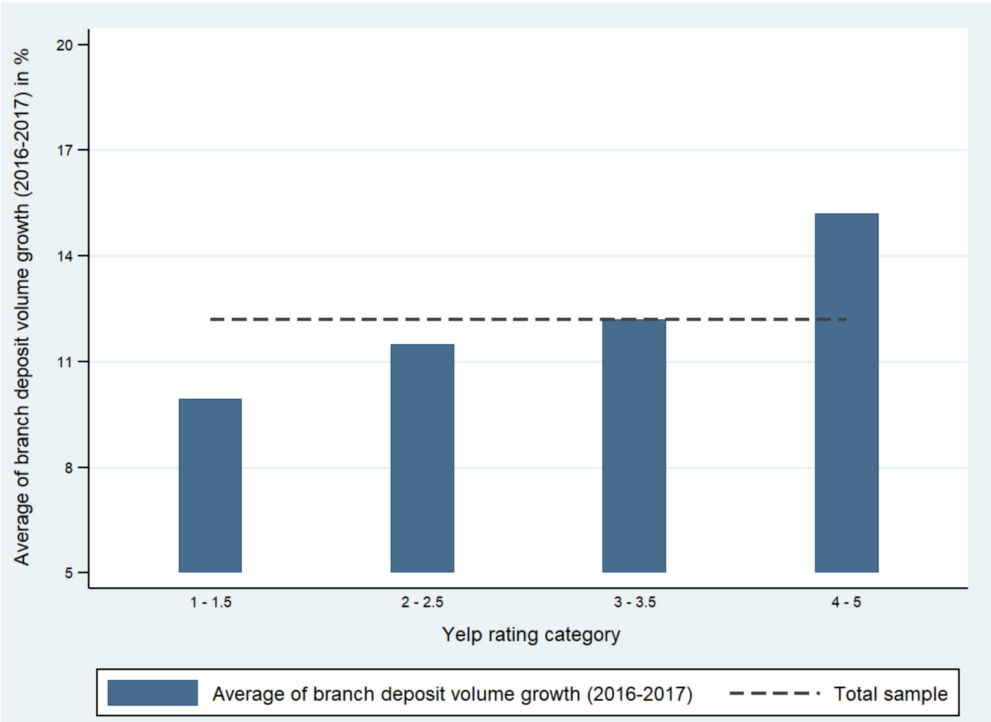


Figure VIII: Regression discontinuity design - Graphical analysis

The figure shows the average bank branch deposit volume growth (blue dots) from June 2016-June 2017 within a +/- 0.15 bandwidth around discontinuity rounding thresholds of Yelp ratings. Deposit volume growth is calculated as the change in percentage decimals (1% = 0.01) in deposit volumes from June 2016-June 2017 of each branch in the sample. The *unrounded* Yelp rating is measured continuously from 1 (worst rating) to 5 (best rating) and calculated as the *unrounded* average of all bank branch ratings received. The bottom-right diagram combines all discontinuity subsamples based on standardized values of the unrounded Yelp ratings.

Appendix

Table A-I: List of sample bank branches by counties/ states and rating category

The table shows the number of bank branches included in the total sample sorted by their location county/ state and by Yelp rating category. The bank branch Yelp rating is measured from 1 (worst rating) to 5 (best rating) in 0.5 increments. The rating is calculated as the average of all ratings received rounded to the nearest increment. Bank branches which are not rated on Yelp in June 2016 are counted as "No Yelp rating". "High Yelp rating" branches are defined as being rated 4, 4.5 or 5. Otherwise, i.e., in case of "Low Yelp rating" branches, Yelp ratings of 1-3.5 are included.

County	No Yelp rating	Low Yelp rating	High Yelp rating
Allegheny	385	18	5
Cabarrus	39	2	1
Champaign	80	6	1
Clark	118	179	42
Cuyahoga	369	15	3
Dane	139	9	2
Gaston	48	1	0
Lorain	79	1	2
Maricopa	436	274	80
Mecklenburg	182	35	4
Summit	151	0	1
Union	36	2	0
Total	**2062**	**542**	**141**

State			
Arizona	436	274	80
Illinois	67	6	1
North Carolina	305	40	5
Nevada	118	179	42
Ohio	612	16	6
Pennsylvania	385	18	5
Wisconsin	139	9	2
Total	**2062**	**542**	**141**

Table A-II: List of sample bank branches by bank and rating category

"High Yelp rating" ("Low Yelp rating") branches are defined as being rated 4, 4.5 or 5 (1-3.5).

Bank name	No Yelp rating	Low Yelp rating	High Yelp rating
Academy Bank, National Association	4	0	0
Alerus Financial, National Association	0	0	1
Alliance Bank & Trust Company	3	0	0
American First National Bank	1	0	0
Ameriserv Financial Bank	1	0	0
Aquesta Bank	4	0	0
Arizona Bank & Trust	4	0	3
Armed Forces Bank, National Association	1	1	0
Associated Bank, National Association	15	1	1
Badger Bank	1	0	0
BANK 34	2	0	0
Bank Mutual	3	0	0
Bank of America, National Association	45	144	11
Bank of Deerfield	2	0	0
Bank of George	2	0	0
Bank of Rantoul	2	0	0
Bank of Sun Prairie	4	0	0
Bank of the Ozarks	7	0	0
Bank of the West	4	1	0
BankChampaign, National Association	1	0	0
Bankers' Bank	1	0	0
Bankers Trust Company	1	0	0
Beal Bank USA	2	0	0
Beal Bank, SSB	2	0	0
Belmont Federal Savings and Loan Association	1	0	0
BlueHarbor Bank	1	0	0
BMO Harris Bank National Association	51	4	0
BNC National Bank	2	0	0
BNY Mellon, National Association	1	0	0
Bofi Federal Bank	1	0	0
BOKF, National Association	4	0	0
Branch Banking and Trust Company	49	4	1
Brentwood Bank	5	0	0
Buckeye Community Bank	1	0	0
Busey Bank	10	3	0
Capital Bank Corporation	8	0	0
Capitol Bank	2	0	0
Carolina Premier Bank	0	0	1
Carolina Trust Bank	1	0	0
Cathay Bank	0	1	0
Cedar Hill National Bank	1	0	0
Chemical Bank	7	0	0
CIBM Bank	2	1	0
Citibank, National Association	1	7	1
Citizens Bank of Pennsylvania	68	2	0
Citizens Bank, National Association	61	0	0
City National Bank	4	0	0
Civista Bank	2	0	0
CoBiz Bank	3	0	0
Comerica Bank	15	0	2
Commerce Bank	1	0	0
Commerce Bank of Arizona	1	0	0
Community Bank	1	0	0
Compass Bank	32	10	4
Compass Savings Bank	1	0	0
Credit First National Association	1	0	0
Credit One Bank, National Association	0	2	0
Dewey Bank	1	0	0
DMB Community Bank	2	0	0
Dollar Bank, Federal Savings Bank	53	3	0
East West Bank	1	0	0
Enterprise Bank	1	0	0
Enterprise Bank & Trust	2	0	0
Farmers & Merchants Bank	2	0	0
Farmers & Merchants State Bank	1	0	0
Farmers Savings Bank	1	0	0
Fifth Third Bank	85	4	0
FineMark National Bank & Trust	2	0	0
First American Trust, FSB	2	0	0
First Bank & Trust	4	0	0
First Business Bank	1	0	0
First Commonwealth Bank	31	0	1
First Federal Savings and Loan Association of Lakewo	15	1	0
First Federal Savings and Loan Association of Lorain	4	0	0
First Federal Savings Bank of Champaign Urbana	2	0	0
First Fidelity Bank	5	1	0
First Financial Bank, National Association	5	0	0
First Foundation Bank	1	0	0
First International Bank & Trust	2	0	1
First Mid-Illinois Bank & Trust, National Association	3	1	0
First Midwest Bank	1	0	0
First National Bank of Pennsylvania	70	1	0
First National Bank Texas	11	2	0
First Niagara Bank, National Association	0	1	0
First Savings Bank	1	0	0
First Security Bank of Nevada	0	1	0
First State Bank	1	0	0
First Western Trust Bank	2	0	0
FirstBank	13	3	1
First-Citizens Bank & Trust Company	29	0	0
Firstmerit Bank	0	0	1
FSNB, National Association	1	0	0
Gateway Commercial Bank	0	0	1
Goldwater Bank, N.A.	1	0	0
Grandpoint Bank	1	0	0
Great Midwest Bank, S.S.B.	1	0	0
Great Western Bank	1	0	0
Heartland Bank and Trust Company	4	0	0
Hickory Point Bank and Trust	1	0	0
Home Savings Bank	5	0	0
HomeTrust Bank	2	0	0
Horizon Community Bank	1	0	0
Independence Bank	1	0	0
Iroquois Federal Savings and Loan Association	1	0	0
Johnson Bank	8	0	0

Bank name (continued)	No Yelp rating	Low Yelp rating	High Yelp rating
JPMorgan Chase Bank, National Association	98	125	36
KeyBank National Association	103	3	0
Kirkwood Bank of Nevada	2	0	0
KS StateBank	1	0	0
Longview Bank	4	0	0
Marine Bank	2	0	0
Mars Bank	1	0	0
McFarland State Bank	3	0	1
Meadows Bank	3	0	0
Mechanics & Farmers Bank	1	0	0
Metro Phoenix Bank	1	0	0
MidCountry Bank	1	0	0
MidFirst Bank	11	6	8
Midland States Bank	1	0	0
Monona Bank	7	1	0
Mound City Bank	1	0	0
Mutual of Omaha Bank	7	0	0
National Bank of Arizona	0	2	0
Nevada Bank and Trust Company	1	0	0
New York Community Bank	34	1	1
NewDominion Bank	1	0	0
Nextier Bank, National Association	4	1	0
Northwest Bank	31	0	1
Oak Bank	0	1	0
Old National Bank	17	0	0
Opus Bank	2	0	0
Oregon Community Bank & Trust	2	0	0
Paragon Commercial Bank	1	0	0
Park Sterling Bank	12	0	0
Parkway Bank and Trust Company	8	0	0
Peoples Bank	8	0	0
Perpetual Federal Savings Bank	1	0	0
Philo Exchange Bank	2	0	0
Pinnacle Bank	6	0	2
PNC Bank, National Association	161	11	3
Regions Bank	3	1	0
RepublicBankAz, N.A.	1	0	0
River Valley Bank	1	0	0
Royal Business Bank	1	0	0
S&T Bank	12	0	0
Settlers Bank	1	0	0
Sewickley Savings Bank	3	0	0
Slovak Savings Bank	1	0	0
South State Bank	3	0	0
Soy Capital Bank and Trust Company	1	0	0
Standard Bank, PaSB	9	0	0
Starion Bank	3	0	0
State Bank of Bement	1	0	0
State Bank of Cross Plains	8	0	0
Stearns Bank National Association	0	1	0
SunTrust Bank	29	0	0
TCF National Bank	4	3	0
The Apple Creek Banking Company	1	0	0
The Bank of New Glarus	1	0	0
The Bank of New York Mellon	1	0	0
The Edgar County Bank and Trust Co., Paris, Illinois	2	0	0
The Farmers National Bank of Canfield	2	0	0
The Farmers National Bank of Emlenton	1	0	0
The Farmers Savings Bank	1	0	0
The Fidelity Bank	2	0	0
The First Central National Bank of St. Paris	3	0	0
The First National Bank of Berlin	1	0	0
The Fisher National Bank	2	0	0
The Gifford State Bank	3	0	0
The Huntington National Bank	128	4	4
The Middlefield Banking Company	3	0	0
The Northern Trust Company	4	0	0
The Park Bank	13	0	0
The Park National Bank	4	0	0
The Peoples Community Bank	1	0	0
The Peoples Savings Bank	2	0	0
The Pioneer Savings Bank	1	0	0
Third Federal Savings and Loan Association of Clevel	15	2	0
Town & Country Bank	4	0	0
Town Bank	1	0	0
Toyota Financial Savings Bank	1	0	0
Tristate Capital Bank	2	0	0
TrustBank	3	0	0
U.S. Bank National Association	139	39	17
UMB Bank, National Association	7	0	0
Union Bank & Trust Company	2	0	0
Union Federal Savings and Loan Association	1	0	0
Unison Bank	1	0	0
United Community Bank	1	0	0
USAA Savings Bank	0	1	0
Uwharrie Bank	2	0	0
Valley Bank of Nevada	1	0	0
Washington Federal, National Association	17	0	1
Wells Fargo Bank, National Association	142	124	34
WesBanco Bank, Inc.	17	0	0
West Valley National Bank	3	0	0
West View Savings Bank	4	0	0
Western Alliance Bank	13	2	1
Western State Bank	2	1	0
Westfield Bank, FSB	3	0	0
Wilmington Savings Fund Society, FSB	2	0	0
Wisconsin Bank & Trust	3	0	0
Woodforest National Bank	20	0	0
ZB, National Association	29	14	2
Total	**2062**	**542**	**141**
% of branches by banks represented in all categories	55.3%		

Curriculum Vitae

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