Intangible Customer Capital and Bank Resilience*

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Abstract

Bank stability depends critically on the ability to connect and retain customers amid negative shocks. This study proposes a novel measure of accumulated customer capital at the branch level. In a within-bank-county estimation, we exploit reputation damage as exogenous negative shocks to deposit-taking and find that branches with higher customer capital mitigate deposit outflows more effectively. These results are stronger in neighborhoods with higher income and lower population mobility, and for branches of community banks. Overall, our work highlights the value of intangible customer capital as a novel and important factor influencing the resilience of retail banking relationships.

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1 Introduction

Customer capital, the intangible capital embodied in the relationships that a firm has with its customers, is an important component of firm economic value. Reflecting the recognition of a company's products and services, customer capital has a significant impact on the company's durable advantages over competitors (Bronnenberg, Dubé, and Gentzkow (2012)), financial performance (Gourio and Rudanko (2014)), and stock returns (Rudanko et al. (2017), Dou et al. (2021)).

While customer capital is important for a wide range of firms, we expect it to be particularly relevant for banks, in that banks are relationship driven and the resilience of banking relationships depends critically on banks' ability to retain customers amid systematic or idiosyncratic shocks. Existing literature largely frame bank resilience as a function of tangible items on the balance sheet, such as regulatory capital (i.e., Basel III capital adequacy requirements), Z-score (Boyd and Runkle (1993), Laeven and Levine (2009), Houston et al. (2010)), and default risk (Nagel and Purnanandam (2020)). In recent years, the importance of intangible capital has received growing attention from academics and practitioners. Notably, Drechsler, Savov, and Schnabl (2017) model the "percentage of non-switching customers" as a major determinant of banks' local market power. McKinsey (2019) also highlights the value of customer capital as branches transform into a more consultative role featuring personalized offers. However, researchers have struggled to empirically quantify the link between intangible capital and bank resilience. Our study presents the first empirical evidence showing that a bank's accumulated customer capital has a substantial impact on securing a steady stream of customers amid adverse demand shocks.

Specifically, we explore the value of bank customer capital by quantifying, for the first time, the quality of customer engagement at the branch level. We utilize a novel database - the Google Map Cloud Platform, which provides a staggering amount of information including customer ratings and detailed reviews for over 150 million physical locations around the world. As the most popular search engine in the world, Google has built trust and credibility among global customers. A recent survey shows that 77% of consumers are willing to leave a review when asked, and 81% of consumers visited Google reviews in the past year.[1] In this study, we focus on retail banking

[1] "Podium 2017 State of Online Reviews," `https://learn.podium.com/rs/841-BRM-380/images/Podium-2017-State-of-Online-Reviews.pdf`.

locations and obtain 699,008 reviews on 75,903 unique bank branches in the United States. We use customers' average rating on the branch's services and product offerings as a proxy for the branch's accumulated customer capital ('ACC', hereafter).[2]

Arguably, a key component of a bank's value is its ability to attract a stable set of core deposits that largely remain in place in the face of a variety of possible economic shocks. With this point in mind, we utilize this novel database to explore how ACC influences the resilience of retail banking relationships. More specifically, in a two-stage framework, we first identify a set of reputation shock events that disrupt a bank's deposit-taking, and then examine how ACC helps mitigate the negative impacts of these shocks at the branch level.[3] The extant literature on depositor discipline has demonstrated reputation damage as a valid idiosyncratic shock to deposit-taking. Notably, Homanen (2018) and Chen, Hung, and Wang (2019) find that depositors withdraw funds when observing banks' negative ESG practices, due to a loss of trust or dissatisfaction with the banks' non-ethical policies. In this study, we create the set of reputation shock events using the RepRisk database, which tracks negative news on banks' business conducts and their treatments of various stakeholders including customers, employees, environments, and communities.

Our validation tests confirm that branch deposit growth subsides following negative news coverage, and the magnitude of the impact increases with the severity of the incidence. We include branch fixed effects (FEs, hereafter) to preclude the impacts of time-invariant branch-level omitted variables (e.g., geographical locations or proximity to businesses), and county-year FEs to exclude the effects of time-varying county-specific events (e.g., political elections or natural disasters). Economically, depending on the severity of the incidence, the deposit growth rate is 0.7 to 2.6 percentage points lower following reputation shocks.[4] Our results suggest that bank customers penalize banks for behaviors that are perceived to be detrimental to stakeholders, and demonstrate the validity of using negative ESG incidents as a unique, quasi-exogenous empirical setting to examine the

[2]Existing measures of customer capital are firm- or brand-level measures based on either brand valuation surveys (e.g., BAV brand perception survey as in Larkin (2013) and Dou et al. (2021)) or advertising expenses (Belo, Lin, and Vitorino (2014)).

[3]We focus on deposits because deposit-taking is one of the most critical retail banking functions. According to the FDIC, deposits represent 81% of banks' total liabilities (Q4 2020, *Quarterly Banking Profile* Report). Additionally, we also examine residential mortgages in Section 5.4. Thus, we investigate the resilience of retail banking relationships using two representative banking products from both the asset and liability sides of the balance sheet.

[4]The average deposit growth rate during our sample period is 9.4 percentage points (see Table 1).

resilience of retail banking relationships as a function of ACC.[5]

Building on the negative relationship between deposit growth and adverse reputation shocks, we examine the resilience of retail banking relationships when these shocks ripple through branch networks. Specifically, we explore whether branches with higher levels of ACC (i.e., customer rating) are more resistant to bank-level reputation shocks. Theoretically, the direction of the impact remains unclear. One possibility is that higher-rated branches have "more to lose." Specifically, these branches may have accumulated more social acceptance and trust through their customer interactions, which may subsequently be perceived by customers as deceptive or illusive when they find the bank is involved in business misconducts (expectations lead to disappointments). If so, then higher-rated branches may experience a larger drop in deposit growth following an adverse reputation shock. Alternatively, higher-rated branches may have successfully accumulated sufficient local goodwill to resist the negative impact. This view assumes that branches may possess some distinctive advantages unique to the branch and independent of the parent bank, exemplified by decentralized banks with more decision-making delegation. Indeed, previous literature has documented that the value of local information and interactions increases during turbulent macro shocks (the "localist" view. See Aghion et al. (2021)). This view predicts that investments in local customer banking experiences help protect branches against future hits to their parent bank's reputation.

Our results are consistent with the latter expectation. Conditional on a reputation shock, we find a positive and significant cross-sectional relationship between ACC and deposit growth. A one-standard-deviation increase in branch-level ACC is associated with an increase in deposit growth of 0.3 to 0.5 percentage points, thereby attenuating the negative impact of reputation shocks by 16.32% to 49.86%. In contrast, we do not find a significant relationship between ACC and deposit growth for branches of unshocked banks. Consequently, we offer strong evidence that banks with stronger levels of ACC are better positioned to withstand the shocks to their reputation.

Admittedly, an empirical examination of the connections between ACC and the resilience of retail banking relationships is subject to two identification challenges: measurement errors and

[5]We focus on negative ESG news as negative shocks to deposit-taking, but have not included positive ESG news as positive shocks for two reasons. First, literature (e.g., Chen, Hung, and Wang (2019)) does not find evidence showing that depositors respond to positive ESG shocks. Second, positive ESG news are more likely to be strategic and subject to green-washing bias.

omitted variables. Measurement errors arise because the utility functions of the retail clientele for different branches may be different. In those cases, the ratings and reviews are not comparable across branches. Omitted variables are also a valid concern when time-varying bank-county unobserved variables are associated with both ACC and branch deposit growth. For example, when a bank is planning to retreat from a local market, the decision may reduce both its commitment to customer services and its efforts for keeping deposit growth. Reserve causality is unlikely a major concern in this study because bank reputation shocks and the exact timing of news reports by outsiders are arguably quasi-exogenous and outside the control of corporate insiders. The likelihood of changes in branch deposit growth reversely leading to negative news coverage initiated by outsiders is extremely low.

We alleviate these endogeneity concerns by conducting a within bank-county-shock estimation. This extremely restrictive setup allows us to observe how different branches of the same bank operating in the same geographic region differentially respond to a common reputation shock, and how these responses depend on the branches' levels of ACC. The identifying assumption for this estimation is that customers with similar preferences and utility functions cluster by bank and location, and therefore the ratings by reviewers connected to the same bank in the same county are more comparable. Furthermore, high dimensional bank-county-shock FEs help us preclude the impact of time-varying bank-county specific omitted variables. Admittedly, there remains some heterogeneity across different neighborhoods within the same county. With this concern in mind, we also check the robustness of our results by using even more granular bank-ZIP Code-shock FEs to preclude the impact of time-varying neighborhood-specific variables, and confirm that our results still persist.

Another factor that may affect the consistency of our estimation and the interpretation of the results is the rise of digital channels in banking. Admittedly, the average customer rating only reflects customer perception of in-branch services and products, and one may argue that customer capital is also accumulated through digital channels. We believe that this consideration is unlikely to confound our estimations for two reasons. First, based on the observations from practitioners, increase in deposit-taking activities is primarily linked to physical branch visits. According to McKinsey (2019), among customers that opened a core banking product in the past two years (e.g., checking account), only 13% acquired them digitally. Deloitte (2020) echoes the findings by showing that most customers prefer branches over digital channels when opening new accounts for both simple (e.g., savings accounts and debit cards) and complex products (e.g., loans). Second, the customer capital accumulated through digital channels do not vary across branches operated by the same bank in the same year. Given that we employ a within-bank-county regression, this common digital component of customer capital is unlikely to explain the variations in our dependent variable (i.e., deposit-taking).

To shed some light on the potential drivers of our results on ACC, we document the heterogeneous effects of ACC across counties with differential socioeconomic conditions. First, we find a stronger effect of ACC in counties with higher income per capita, suggesting that wealthier customers place a higher economic value on non-price factors, such as established customer connections. Second, we find a stronger effect of ACC in counties with lower population mobility, measured by the share of the population that migrates into or out of the county during our sample period. Given that deposit growth can be driven by retaining existing customers and/or attracting new customers, our results indicate that ACC may have a larger impact on the stickiness of existing customers following adverse shocks.

We further investigate the heterogeneous effects of ACC by comparing the results between community banks and large regional or super-regional banks. We posit that effective customer interactions are more crucial for community banks that rely more on relationship banking using soft information collected through years of experience with local customers and business communities. Indeed, we find that the effects of ACC are stronger among branches that are part of a community bank, and the results are robust to alternative asset cutoffs.

Our analysis of depositor decisions suggests that banks with higher levels of ACC build more resilient relationships and are better positioned to confront the effects of adverse reputation shocks. However, the multi-faceted customer banking experience remains a black-box that is only partially captured by the aggregate branch-level ACC. It remains unclear what customers truly value and what dimensions of customer interactions consequently contribute to the resilience of retail banking relationships. Thus, we decompose the customer banking experience by analyzing the detailed textual reviews that form the basis of Google ratings. In this analysis, we follow Li et al. (2020) to employ a semi-supervised machine learning-based approach to extract key topics from the underlying textual reviews. We highlight four main dimensions that drive ACC: 1) accessibility of the services, 2) quality of the products, 3) hospitality of the staff, and 4) quality of the facilities. For each branch, we construct indicators that measure the extent to which customers care about each dimension.

We employ the decomposed topic-specific ACCs to examine the aspects of products and services that depositors care most about in the wake of reputation damage. We find that the accessibility dimension, which captures the efficiency, hours, and locations of branch operations, is the key factor that drives customer retention. These results suggest that the relative accessibility of branch services determine the customer's effective switching costs. Notably, pricing and fee-related features of products do not play a role in retaining customers after adverse shocks.

While our results show that higher levels of ACC help retain depositors following adverse reputation shocks, the impact of ACC can go above and beyond depositor retention to borrower growth. As a final robustness test, we also consider an alternative set of tests where we focus on the demand for residential mortgages. Following Cortés and Strahan (2017) and Dlugosz et al. (2019), we employ natural disasters as positive shocks to local residential mortgage demand, and explore whether higher levels of ACC enable banks to capture additional mortgage business in the aftermath of these natural disasters.

We find that, although natural disasters generate an average increase in mortgage demand, the increase is significantly larger for banks with higher levels of ACC. For banks with local ACC at the top (bottom) tercile among all bank-county observations within the state, the number of mortgage applications increased by 55.8% (35.5%) in the disaster year. The result is robust to loans of different purposes, which arguably contain different proportions of new and returning customers. Our results indicate that banks with higher levels of ACC are better positioned to capture stronger mortgage growth in the face of positive demand shocks. With respect to topic-specific ACCs, we find that hospitality of the staff and the quality of facility are the two main drivers of new business. These findings demonstrate that the "human element" has an important impact on the establishment of retail banking relationships during turbulent and uncertain periods following natural disasters. Altogether, these results provide further evidence that ACCs offer useful insights into customer attitudes, and that these attitudes meaningfully affect a bank's ability to retain and attract customers in the aftermath of reputation shocks and natural disasters.

Our results contribute to several distinct, but interconnected literature. Our study adds to the foundation works on customer capital by Gourio and Rudanko (2014), Rudanko et al. (2017) and Dou et al. (2021).[6] The existing literature typically uses survey-based data (Loveman (1998), Huang and Sudhir (2021)) whose time window, customer base, or the number of banks covered are relatively limited. Our massive textual customer review data covering a large number of bank branches allow us to examine a novel and important research question - how to quantify intangible customer capital and evaluate its impact on bank resilience.

Second, our paper contributes to the evolving literature on the social responsibility of banking institutions. There are ongoing concerns about the responsiveness of companies to consumer and community needs. These concerns are particularly pronounced in key regulated areas such as banking. Different banks likely have different views on the relative importance of these issues, and these views may ultimately influence a bank's willingness to invest in its "social capital". (Chava (2014), Homanen (2018), Houston and Shan (2021)). In this regard, our study yields particular insights into the specific factors that matter most to customers and that lead to more resilient relationships.

Third, our paper highlights another important factor that influences the strength and resilience of banking relationships. In this vein, our work is related to the long-standing theories of relationship lending (e.g., Sharpe (1990), Berger and Udell (1995), Puri and Rocholl (2008)) and depositor behavior (e.g., Iyer and Puri (2012), Iyer, Puri, and Ryan (2016)). Relatedly, our results also indicate that ACC is an important non-price factor influencing the establishment and resilience of retail banking relationships. In this regard, our paper contributes to the literature that has documented that other non-price factors affect banking relationships, such as political orientation (Khwaja and Mian (2005)), reputation (Ross (2010), Gopalan, Nanda, and Yerramilli (2011), Chava (2014)), and cultural and legal origins (Mian (2006), Giannetti and Yafeh (2012)).

Fourth, our paper sheds light on the role of traditional bank branches in the digital era.

[6] Recent work by Huang (2021) presents the first evidence on the financial consequences of customer satisfaction. The paper documents that small businesses with higher ratings are more likely to be approved for small business loans.

Branches, as the traditional banking channel, play a key role in bank-customer interactions. Despite the continued pressure of digitization, local bank branches still have inherent advantages in facilitating access to credit (Nguyen (2019)), building brand presence (Jacques et al. (2018)), and maintaining customer relationships (Larsson and Viitaoja (2017)). Moreover, customers appear to place more trust in businesses with whom they have a good rapport, and arguably these links are even more important when the business specializes in complex financial products (Buttle and Maklan (2019)). Indeed, survey data show that the effects of customer satisfaction with branches on overall satisfaction are at least twice as large as satisfaction with online or mobile channels (Srinivas and Wadhwani (2019)). To this extent, our results highlight the apparent benefits of human interactions in maintaining durable customer relationships and suggest that there may be risk associated with a quick overreliance on technology. Moreover, our findings may indicate an ongoing niche role for smaller community banks that utilize human interactions to build and maintain customer capital.

2 Data

2.1 Accumulated Customer Capital (ACC) - Google Map Cloud Platform

We measure the branch-level accumulated customer capital, namely the customers' perception of a branch's services and products, using its average Google rating. We obtain 699,008 reviews on 75,903 unique bank branches in the United States from Google Map. The Google Map Platform is built with the most comprehensive, global points of interests data. With its online review and photosphere systems, Google Map provides real-world insights and immersive location experiences for over 150 million physical locations around the world. The service was first offered to Android and iOS users in September 2008. In 2013, it has grown into the most popular App with 54% of global smartphone users using it at least once.[7] In this study, we focus on the Google profiles observed since 2015, when the service expanded to a sizable user base to ensure that banking experiences are widely and actively shared on the platform.

[7] "Top Global Smartphone Apps," https://blog.gwi.com/chart-of-the-day/top-global-smartphone-apps-who-s-in-the-top-10/.

To construct the database, we first extract the list of bank branches from the 2019 FDIC Summary of Deposits (SOD) file. We locate the Google profile of each branch by searching the combination of bank name and branch address as the key words in the Google search engine. This automated process is programmed in Python and enabled by the Wextractor Google Map API. After identifying the Google profile of each branch in the Google Map Platform, we download the rating, time and the textual content of all reviews. The downloading process was performed during March 2020, and our sample covers all reviews left as of December 2019.

Figure 1A documents the number of reviews by quarter. The growing popularity of Google Map over the past few years has brought the quarterly number of reviews on bank branches from 4,834 in 2015Q1 to 46,480 in 2019Q4. However, the influx of new users and new reviews do not significantly change how people rate their banking experiences over time. Figure 1B shows that the national average branch ratings are largely stationary. It is not surprising given that how banks interact with customers is unlikely to change significantly during our sample period. In light of this observation, we exploit the cross-sectional heterogeneity in customer ratings of banking experience, rather than the time-series variation, in our empirical analysis.

In order to decompose the ratings along different dimensions, we further tokenize and clean the textual content of the reviews by removing 1) punctuation, 2) numbers, 3) non-English words, and 4) stop words using the NTLK list of English stop words. Finally, we only keep reviews with more than three words after these cleaning steps. We record the number of words in each review as the length of the review. The yearly proxy for the accumulated customer capital (ACC) is calculated as the average of all ratings of the branch as of every June 30.[8]

There are two reasonable concerns about the Google Map Platform database: noise and coverage. Both are common for crowd-sourced review systems. The first relates to the existence of an extremely emotional customer whose review could be noisy and less informative. We argue that as long as the probability of a branch receiving a "random" review is not significantly different from that of another branch operated by the same bank in the same neighborhood, then a cross-sectional

[8]We obtain the yearly average rating as of every June 30 because we need to match the ratings to deposit growth obtained from SOD, which is reported every midyear. In the robustness test section, when we use mortgage outcomes instead of the deposit growth as the dependent variable, we calculate the yearly Google rating as of every December 31.

comparison of the ratings within the same bank-county-year is informative.[9]

The second issue relates to the availability of reviews. Not all branches have reviews, and even for the same branch, the start year of the Google profile varies. With this limitation in mind, we restrict our sample to the branches with non-missing ratings. Furthermore, we only compare the ratings of branches operated by the same bank, in the same county, and observed in the same year. We also include the yearly number of Google ratings ($NumReviews$) as an additional control variable in our empirical analysis, as the availability of reviews may be correlated with the level of rating itself.

2.2 Reputation Shocks

This study measures a bank's perceived reputation related to ESG and business conduct issues using the RepRisk database. The database tracks negative news incidents of firms from January 2007 to June 2019. A dedicated team of analysts leverage a combination of artificial intelligence and curated human analysis to track a universe of over 95,000 firms globally. Over 80,000 public sources and stakeholders in 20 languages are screened on a daily basis. Once an incident is identified, analysts conduct additional analysis to (1) confirm that the incident is indeed related to the firm's ESG activities or business conduct, (2) remove possible duplicate media coverage on the same incident to make sure each risk event only enters once into the RepRisk Platform, and (3) identify the specific nature of the incident, by mapping it to 28 issues and 45 topics including "discrimination in employment", "controversial products", and "tax evasions", etc. Each incident is assigned three proprietary scores based on severity (harshness), reach (influence), and novelty (newness). Finally, the monthly RepRisk Index is updated, reflecting the ensuing impact of the news incident on the firm's perceived reputation. The RepRisk Index is a non-broken, time-series variable ranging from 0 to 100, with 100 representing the worst perceived reputation.

We capture the reputation shock to a bank by exploiting the jumps in its RepRisk Index. According to RepRisk, the magnitude of the jump increases with the severity of the negative news incident. A yearly increase in the index is driven by the intensity of negative news coverage on the

[9] An intuitive analogy is the teaching evaluations by students. The likelihood of receiving a noisy evaluation is not zero. However, as long as the probability is not different across faculty members teaching similar subjects, then a cross-sectional comparison is still informative.

bank's business conducts and lending practices (Houston and Shan (2021)). Instead of arguing for a "one size-fits-all" threshold, we create four indicator variables that are associated with increasing levels of damage to the bank's reputation - *Rep_10*, *Rep_15*, *Rep_20*, and *Rep_25*, which equal one if the RepRisk Index increases by more than the corresponding magnitudes over the past year, and zero if the jump is less than 10.[10] In addition to indicator variables, we also define a continuous variable, *Rep_Chg*, to capture the reputation damage. It is defined as the maximum jump in the RepRisk Index over the past year. To merge with other databases, we identify the banks' RSSD ID by cross-checking the banks' ISIN and name in the SNL database.

In Figure 2, we use the anecdotal evidence related to Wells Fargo's recent scandals to illustrate how the RepRisk Index reflects negative reputation shocks. The monthly change in the RepRisk Index of Wells Fargo is presented on the vertical axis. The discrete jumps coincide, in severity and in time, with the important events along the timeline of the Wells Fargo account scandal. This anecdotal evidence lends support to using changes in the RepRisk Index to identify idiosyncratic reputation shocks of banks.

2.3 Branch Deposits

We obtain branch office deposits data from the FDIC Summary of Deposits (SOD) database. SOD reports the annual survey of branch office deposits as of June 30 for all FDIC-insured depository institutions.[11] Besides branch deposits, the survey also reports comprehensive data including branch location, date of establishment, institution type, and name of the top holding company, etc. We construct the following variables using SOD data: the amount of branch deposits (*Deposits*); the annual growth in branch deposits (*DepositGrowth*); a local bank dummy (*Local*) that equals one if a bank obtains more than 65 percent of its deposits from a single county, and zero otherwise;

[10] In Table 5, we examine the validity of the measures by regressing deposit growth on the proxies of reputation shock. The economic magnitudes of the indicator variables increase in the magnitude of jumps in the RepRisk Index, even after controlling for branch and county-year FEs. Details of the validity tests are reported in Section 4.1.

[11] In our study, we assume that the branch that the depositor visits is the same branch where the deposits are assigned. In reality, FDIC allows banks to assign deposits consistent with their existing internal record-keeping practices. The general guidelines are the following: 1) deposits assigned to the office in closest proximity to the account holder's address, 2) deposits assigned to the office where the account is most active, 3) deposits assigned to the office where the account was opened, or 4) deposits assigned to offices for branch manager compensation or similar purposes (*FDIC Summary of Deposits Reporting Instructions*, June 30, 2020). Our assumption is consistent with the first and second guidelines. If banks choose to comply with the 3) or 4) then it creates attenuation bias. In those cases, our results are the underestimation of the true economic effects.

a market share variable ($CountyShare$) that measures the market share of a given bank branch in a given county by deposits; a branch location dummy ($SameState$) that equals one if a branch is in the same state with the headquarter of the bank, and zero otherwise; a new branch dummy (New) that equals one if a branch was established within the past five years, and zero otherwise.

We obtain the branch-level deposit rates data from the RateWatch database. The deposit rates are available for a wide variety of deposit products such as CDs, checking/saving accounts, and money market accounts with different minimum account sizes and maturities. Following Drechsler, Savov, and Schnabl (2017) and Lin (2020), we focus on one of the most popular products - the 12-month CD product with a minimum account size of $10,000. We take the average weekly rates at the branch level during June and July, when the level of deposits in SOD is reported. Then, we construct the following variables: a rate setter dummy ($RateSetter$) that equals one if a branch is a local rate setter and zero otherwise; a better rate dummy ($BetterRate$) that equals one if the average rate of 12-month CD products is higher than the county median, and zero otherwise.

2.4 Bank Balance Sheet and Local Characteristics

A bank's financial conditions such as lending opportunities, profitability, liquidity, and sensitivity to interest rate risk can affect depositors' perception towards the bank. Thus, we control for a rich set of bank financial variables using the data from the Consolidated Report of Condition and Income (Call Report), and calculate the following variables: a small bank dummy ($Small$) that equals one for banks with assets less than two billion dollars, and zero otherwise; the share of loans in total assets ($Loan$); return on assets (ROA) measured as the ratio of annualized net income to gross total assets; liquidity ($Liquidity$) measured as bank cash divided by total deposits; sensitivity to interest rate risk ($Sensitivity$) measured as the ratio of the absolute difference between short-term assets and short-term liabilities to gross total assets. Lastly, we collect the following county-level variables from the American Community Survey (ACS): income per capita ($Income$); population mobility ($Mobility$) measured as the number of people who migrate into or out of the county between 2015 and 2018. Detailed variable definitions are available in Appendix A1. We merge the Google rating data, SOD data, and RateWatch data through the bank branches' RSSD ID, and then merge with the parent banks' reputation shock data and financial condition data using the parent banks' RSSD ID.

2.5 Summary of Statistics

The Call Report-SOD-RateWatch-RepRisk merged sample consists of 135,834 branch-year observations. By year, there are 32,114, 33,454, 35,584 and 34,682 branches from 2015 to 2018, respectively. This sample covers all branches with non-missing deposit level (SOD) and deposit product (RateWatch) information, and requires that their parent banks have non-missing Call Report and RepRisk records. If we further restrict the sample to the branches that have non-missing Google profiles as of every midyear, the sample size decreases to 88,845. This restricted sample is unbalanced because the Google profile was initiated in different years for different branches. There is, unfortunately, not a rule or shock that mandates people to write reviews on their branch visits. Similar to the pattern observed in almost all crowd-sourced review systems, we observe an upward trend in the number of merged branches with non-missing Google profile as of each year. In our sample, there are 11,277, 19,666, 27,569, and 30,333 merged branches from 2015 to 2018, respectively.

In terms of the composition of unique branches and banks, our sample includes 35,978 distinct branches owned by 177 distinct banks. Among the 177 unique banks, 49 have total assets below \$1 billion, 70 have total assets between \$1 billion to \$10 billion, and 58 have total assets above \$10 billion. Thus, while the availability of crowd-sourced systems such as Google inevitably raises selection concerns, our sample is representative in that it is relatively evenly distributed among large, medium and small banks. Table 1 shows that an average branch-year has 3.178 reviews with an average rating of 3.538. The variation in rating is also sizable. The relative standard deviation of rating is 0.332 (1.173/3.538). The mean value for the four reputation shock dummies varies from 18.7% to 55%. The average annual deposit growth of branches in our sample is at 9.4%.

3 Decomposing Measures of Accumulated Customer Capital (ACC)

Our study presents a novel empirical measure of the branch-level ACC, which captures the customers' perception of a branch's services and products. In this section, we provide more insights on this novel measure. In Section 3.1, we estimate branch-level ACC on high-dimensional FEs, and present the R^2 values to understand the exact portion of the variation in ACC that can be explained by observable characteristics. Section 3.2 examines the determinants of branch-level ACC using the merged sample with Call Report and RateWatch. Section 3.3 presents county-, bank-, and review-level validation tests to alleviate concerns on the level of noise in this measure. In Section 3.4, we decompose the ACC measures along four important and interpretable dimensions - two that center on the interpersonal aspects of the banking experience (accessibility and hospitality), and another two that focus on customer perception about in-branch product offerings and facility.

3.1 Variance Decomposition

We regress ACC on a rich set of fixed effects to examine if geographic or bank-specific characteristics explain the variations. In Panel A of Table 2, the dependent variable is the ACC of bank branches observed on December 31, 2019. The bank, county, and bank-county FEs are included in columns 1, 2 and 3, respectively. Results show that bank FEs explain 22.7% of the variations and county FEs explain only 9%. Column 3 shows that 70.4% of the variations remain unexplained for branches owned by the same bank and operating in the same county. Note that we drop singletons when applying high dimensional fixed effects (Correia (2016)), which leads to a drop in the sample size when a greater number of FEs are included.

In Panel B of Table 2, the dependent variable is the ACC of bank branches observed in every year-end from 2015 to 2019 (if non-missing). Time-varying bank and county FEs (column 4 and 5) only explain 11.2% and 5.3% of the variations. Branch FEs (column 3, 7 and 8) explain 62% to 63% of variations, leaving around 37% of variations attributable to within-branch time-series characteristics.

There are two key takeaways from the variance decomposition analysis. First, banking experiences vary significantly among branches, even across those operated by the same bank in the same county. The Google profiles provide a unique opportunity for us to examine the banking experiences at each individual branch. Second, we confirm that branch-level ACCs are largely stationary during our sample period. It is not surprising given that banks' customer service policies (or customers' perceptions on their neighborhood branches) are unlikely to change collectively in a short period of time. Guided by these findings, we focus on exploiting the cross-sectional heterogeneity, rather than time-series variations, in the wake of exogenous shocks to bank deposit-taking.

3.2 Determinants of ACC

We recognize that investing in ACC is an endogenous choice of the bank and branch, and it could be determined by various time-varying bank and branch level characteristics. In this subsection, we examine if the measures of ACC are correlated with observable bank- and branch-level characteristics by estimating the following cross-sectional regression:

$$ACC_i = \Theta \times X_k + \Lambda \times T_i + FE_j + \varepsilon_i, \tag{1}$$

where i indexes branches, k banks, and j counties. The regression is performed at the branch level. The dependent variable is the ACC of branch i observed on December 31, 2019. The independent variables consist of bank (X_k) and branch (T_i) characteristics. Bank characteristics include the *Small* and *Local* dummies. Branch characteristics include *CountyShare*, *RateSetter*, *BetterRate*, *SameState*, and *New* dummies. We include county FEs (FE_j) to capture any unobservable time-invariant county-specific determinants of ACC. Standard errors are clustered at the county level.

Regression results are reported in columns 1 and 2 of Table 3. Within the same county, branches owned by local and small banks have higher levels of ACC than those owned by larger and/or national banks. *CountyShare* is negatively and significantly correlated with ACC, indicating that branch-level ACC is lower in markets where the bank has more monopoly power.[12] *BetterRate* is positively and significantly related to ACC, suggesting that favorable pricing of banking products is an important determinant of ACC. Finally, we show that recently established branches (*New* = 1), and branches located in the headquarter state (*SameState* = 1) have higher levels of ACC. Newer branches generally feature better locations and upgraded facilities, which are preferred by customers. Consistent with Deng and Elyasiani (2008) and Goetz, Laeven, and Levine (2016), branches located in the home state are more intensively monitored by headquarter offices, leading

[12] Some may expect a positive relationship between branch ACC and *CountyShare* because banks with higher levels of ACC may be better able to attract deposits (reverse causality). Although this could be true, the purpose of this subsection is only to explore a relationship between the ACC and the potential deterministic variables, not to establish a (reverse) causality.

to fewer agency problems and a higher accumulation of customer capital.

In columns 3 and 4 of Table 3, we perform a similar analysis using the branch-year panel. We include a branch-year observation in the sample as long as there is non-missing Google rating information as of a given year. We include county-year FEs and cluster the standard errors at the county-year level. The directions of association are consistent for all of the independent variables. Because both the ACCs and independent variables are quite "sticky" overtime, five out of the seven t-statistics of the coefficient estimates are larger when using the panel as the main sample.

The results of the deterministic regressions highlight the importance of including these control variables in our subsequent analysis. If the high-dimensional FEs do not fully absorb the confounding impact of the deterministic variables, we include the un-absorbed variables as additional control variables through the rest of the regression analysis.

3.3 Validation

This subsection validates that our ACC measure indeed captures customers' perception towards a branch's services and products. We present validation tests at the 1) county, 2) bank, and 3) review levels to alleviate concerns on the level of noise in this novel measure.

In Figure 3A, we calculate and visualize the average ACC of bank branches by county. We show that the average ACC of bank branches in the Midwest are higher than those in the Northeast and the West. Also note that branches in suburban and rural areas enjoy higher levels of ACC than those in urban locations. In Figure 3B and 3C, we map out the ACC for the largest and the second largest banks in the U.S. by deposits - JP Morgan Chase Bank and Bank of America. Notably, there is significant overlap in their branching networks, and the services and products of JP Morgan Chase are rated higher in most of the counties. This observation is consistent with the findings of the U.S. National Banking Satisfaction Study (J.D. Power (2019)), which shows a higher overall customer satisfaction score for JP Morgan Chase than for Bank of America.

Lastly, using the sentiment word list developed by Loughran and McDonald (2011), we confirm that the levels of ACC indeed capture how customers feel during their branch visits. We calculate the weights of positive and negative words in each review (frequency of mentions over the length of the review). Then, we obtain the average weight of positive ($Positive$) and negative ($Negative$) words for the reviews received by the same branch as of December 31, 2019, and use them as the proxies for the overall sentiment of customer interactions at the branch.

We also employ the NRC Emotion Lexicon to detect eight emotions of the reviewers: anger, anticipation, disgust, fear, joy, sadness, surprise and trust. Similar to the sentiment analysis above, we calculate the weights of words related to each emotion and then average the weights across all reviews received by the branch as of December 31, 2019 to obtain the eight emotion variables: $Anger$, $Anticipation$, $Disgust$, $Fear$, Joy, $Sadness$, $Surprise$, and $Trust$.

In Table 4, we regress ACC on the proxies for sentiment and emotions. The coefficient on $Positive$ ($Negative$) is positive (negative) and significant at the 1% level. The coefficients on emotion metrics including $Trust$ and Joy are positive and significant at the 1% level, while those on $Sadness$, $Disgust$, $Fear$, and $Anger$ are negative and significant at the 1% level. The results collectively demonstrate that branch-level ACC is an effective measure of how customers perceive their banking experiences.

3.4 Topic-specific ACC

In this section, we disentangle customers' perception towards a branch's services and products along four dimensions. Following Li et al. (2020), we apply Word2Vector, a semi-supervised approach, to extract topics from unstructured textual documents. The Word2Vector algorithm is a word-embedding model that identifies, for each seed word provided by the user, an expanded set of synonyms (Mikolov et al. (2013)). It is based on a simple, time-tested concept in linguistics: Words tend to co-occur with neighboring words with similar meanings (Harris (1954)). For a given word, the algorithm searches for the neighboring words in the textual document and creates a vector matrix consisting of the frequencies of each neighboring word. The model then applies a neural network to reduce the dimension of the matrix to a fixed number. The similarity between any two words in the document can be calculated as the cosine product between the two corresponding vector representations. Lastly, the algorithm performs the bootstrapping process to iteratively associate words gleaned from the document to each seed word. The most similar words (i.e., those with the highest cosine similarity) are considered as an expanded dictionary to the original set of seed words provided by the user.

Specifically, we first sort all words in the reviews by their corresponding frequencies of mentions and manually screen the top 1,000 words through many iterations to understand what customers value. We select five seed words with similar meanings along each dimension from this high-frequency word list. The seed words for Topic 1 consist of “time”, “wait”, “line”, “call”, and “location”, which we label as topic *Accessibility*. The seed words for Topic 2 consist of “communicate”, “assist”, “experience”, “greet”, and “solve”, which we label as topic *Hospitality*. The seed words for Topic 3 consist of “checking”, “mortgage”, “investment”, “rate”, and “fee”, which we label as topic *Product*. The seed words for Topic 4 consist of “building”, “lobby”, “parking”, “facility”, and “atm”, which we label as topic *Facility*. This step leaves us 20 seed words associated with four topics.

For each seed word, we follow Li et al. (2020) to obtain its unique neighboring words in the reviews and their corresponding frequencies of mentions. We define neighboring words as the five words before and after the position of the seed word. The information about neighboring words is condensed into a 100-dimensional vector. We associate the seed words with the words gleaned from the reviews to calculate their cosine products – the top 20 closest synonyms of each seed word from the same topic are pooled together as the expanded dictionary for the topic. In Appendix A3, we report the top words in the expanded dictionary for each of the four topics.[13]

We define the branch-level sub-component ACCs on each of the topics as follows:

$$TopicACC_{i,t,d} = \frac{\sum_{n \in N_{i,t}} \left(\frac{SR_{i,t,n} \times \sum_{b \in B_{i,t,n}} (\P[b \in TD])}{B_{i,t,n}} \right)}{N_{i,t}}, \tag{2}$$

where i indexes branches, t refers to the year of observation of Google profiles, n refers to the review left in the Google profiles, and d refers to the specific topic (*Accessibility*, *Hospitality*, *Product*, or *Facility*). For each branch, we first obtain a list of reviews observed as of the year, $n = 1, 2, ..., N_{i,t}$. For each review, we further break it into a list of words (unigrams), $b = 1, 2, ..., B_{i,t,n}$. TD is

[13] The words in each expanded dictionary are ranked by their $Fweight$, which is reported in column 2 of Appendix A3. For each occurrence of the word, we scale it by the length of the review. $Fweight$ is the sum of all scaled occurrences of the word in the reviews. We also provide the un-scaled number of occurrences, namely the total frequency of mentions $Freq$ in the third column.

the expanded dictionary of the topic. ¶[·] is the indicator function. We adjust the ratings by subtracting the constant number three, re-centering the scale of ratings as [-2, 2] instead of [1, 5], which we denote as $SR_{i,t,n}$. In essence, we calculate the topic loadings in each review (i.e., the frequency of mentions of words in the topic-specific expanded dictionary over the total number of words in the review), and then multiply it with the scaled rating ($SR_{i,t,n}$) assigned to the review. Using the ratings with a re-centered scale, we ensure that this product will be negative if customers rate the branch below the median of the original rating scale (less than 3 out of a [1,5] scale), and positive if otherwise.[14] Lastly, we aggregate the product and divide the sum by the total number of reviews observed as of year t. By construction, the branch's ACC on *Accessibility* is highest if all review ratings are highest, and the reviews only consist of the words from the *Accessibility* expanded dictionary.

In the robustness section, we also construct the following bank-county level sub-component ACCs which are used in regressions of mortgage lending on natural disasters:

$$TopicACC_{k,j,t,d} = \frac{\sum_{n \in N_{k,j,t}} \left(\frac{SR_{k,j,t,n} \times \sum_{b \in B_{k,j,t,n}} (\P[b \in TD])}{B_{k,j,t,n}} \right)}{N_{k,j,t}}, \tag{3}$$

where k indexes bank, and j refers to county. Other variables are defined in the same way as described in the branch-level measure.

4 Empirical Strategies and Results

4.1 Reputation Shock and Deposit-Taking

We first validate the premise of using reputation damage as a shock to branch deposit growth. As described in Section 2.2, we use the RepRisk data to create four indicator variables (*Rep_10*, *Rep_15*, *Rep_20*, and *Rep_25*) that correlate with greater intensity of negative news coverage of the bank. We posit that a branch's deposit flow is a function of the bank's perceived reputation among customers. We validate the relationship between these novel proxies of reputation shocks

[14] Note that subtracting all ratings by a constant number does not change the time-series or cross-sectional variations in branch ratings. This step, however, reduces the measurement errors in the product which is used to construct the decomposed topic-specific ACCs.

and branch-level deposit growth using the following specification:

$$\begin{aligned} DepositGrowth_{i,t} =& \beta_1 Rep\_J_{k,t} + \beta_2 Deposits_{i,t-1} + \beta_3 BetterRate_{i,t-1} \\ &+ \beta_4 CountyShare_{i,t-1} + \beta_5 Loan_{k,t-1} + \beta_6 ROA_{k,t-1} \\ &+ \beta_7 Liquidity_{k,t-1} + \beta_8 Sensitivity_{k,t-1} + FE + \varepsilon_{i,j,k,t} \end{aligned} \tag{4}$$

where i indexes branches, k banks, j counties, and t years. The regression is performed at the branch-year level. The dependent variable is the growth in deposits at branch i in year t. The independent variable, *Rep_J*, is an indicator variable that equals one if the RepRisk Index of the bank which owns the branch increases by more than J (J=10, 15, 20, or 25) over the past year, and zero if the increase is less than 10. By excluding observations whose RepRisk Index jumps between 10 and J, we keep the control group constant, which consists of observations whose RepRisk Index increases by less than 10, such that we sensibly compare the economic magnitudes of coefficient estimates while holding the benchmark largely constant across the regressions.[15] To alleviate concerns about the choice of cutoffs to create the dummy variables, we also replace the dummies with *Rep_Chg*, the bank's maximum jump in the RepRisk Index over the past year. In our regressions, we also include several lagged time-varying branch- and bank-level control variables: *Deposits*, *BetterRate*, *CountyShare*, *Loan*, *ROA*, *Liquidity*, and *Sensitivity*.[16]

Liberal use of FEs in the regressions further mitigates the confounding effects from other omitted variables. Branch FEs preclude the impacts of time-invariant branch-level characteristics, such as its location/proximity to area businesses. County-year FEs rule out the possibility that any county-specific events, such as political elections or natural disasters, bias our estimation. Standard errors are clustered at the branch level.

Regression results are presented in Table 5. The coefficients of *Rep_J* are negative and statistically significant at the 1% level in all columns. Economically, according to column 4, the deposit growth at branches of banks with a reputation shock (*Rep_25*=1) is lower than the branch mean

[15] In Appendix A4, we redefine *Rep_J* as an indicator variable that equals one if the RepRisk Index of the bank increases by more than J (J=10, 15, 20, or 25) over the past year, and zero if the increase is less than J. Our main results are robust to these variations - the direction of association is the same, and the statistical significance also holds in all columns except in column 3. However, weaker results are expected compared with Table 5 because the control groups also include banks with reputation shocks.

[16] We exclude *SameState*, *New*, and *RateSetter* from the control variables because there is no (or little) variation in these variables within the fixed effects cluster (i.e., branch FE).

by 2.6 percentage points, equivalent to 27.66% of the mean deposit growth (9.4 percentage points). We present the magnitudes of the coefficients and their corresponding 95% confidence interval in Figure 4. We show that the economic magnitudes of the coefficient estimates increase with J, in line with our hypothesis that greater intensity of negative news coverage is associated with more deposit outflows. Our results confirm the impact of negative ESG performance on depositors' funding decisions, consistent with Homanen (2018) and Chen, Hung, and Wang (2019).[17]

4.2 ACC and Bank Resilience amid Negative Demand Shocks

Building on the findings from Homanen (2018) and the results in Section 4.1, we adopt an event study approach to further examine how ACC mitigates deposit outflows. We focus on the banks that have experienced a reputation shock and exploit the heterogeneous levels of ACC among branches operated by the same affected bank in a given area. The specification is as follows:

$$\begin{aligned} DepositGrowth_{i,t} = & \beta_1 ACC_{i,t} + \beta_2 NumReviews_{i,t} + \beta_3 Deposits_{i,t-1} \\ & + \beta_4 BetterRate_{i,t-1} + \beta_5 CountyShare_{i,t-1} + \beta_6 New_{i,t-1} \\ & + \beta_7 RateSetter_{i,t-1} + FE + \varepsilon_{i,t} \end{aligned} \tag{5}$$

where i indexes branches and t years. The regression is performed at the branch-year level, where branches are the branch offices of banks that has experienced a reputation shock in the past 12 months (an increase in RepRisk index by at least 10, 15, 20, or 25). We employ a restrictive specification using bank-county-shock fixed effects, which allow us to compare the deposit flows of branches within a same bank and a same county during the year of the reputation shock. The analysis precludes the impacts of any time-varying bank and county characteristics on deposit flows. Standard errors are clustered at the bank-county-shock level.

Regression results are reported in Table 6. Each column focuses on a subsample of branches whose parent banks experienced reputation shocks of different intensities (J=10, 15, 20, or 25, respectively). We find that deposit growth increases with the branch-level ACC. The coefficient

[17] Despite the restrictive fixed effects in our model, it is likely that the results are predominantly driven by a few major banking scandals in recent years, e.g., Wells Fargo account fraud scandal. To check the robustness of our results, we drop the Wells Fargo reputation shocks from the RepRisk sample and rerun the regressions. The results are quantitatively and qualitatively similar.

estimates on *ACC* are positive and statistically significant at the 1% to 5% levels in columns 1 to 3. The economic magnitudes are sizable. Take column 2 for example, conditional on the reputation shock, a one-standard deviation increase (1.173) in the branch's ACC is associated with a 0.473 percentage points increase in deposit growth ($1.173 \times 0.403\% = 0.473\%$). Even though the coefficient estimate in column 4 is not statistically significant, the economic magnitude remains comparable to earlier results in columns 1 to 3. Chen, Hung, and Wang (2019) show that negative bank social performance reduces depositors' willingness to finance the bank by decreasing their trust in banks. Our results suggest that, higher levels of ACC built at the branches may help mitigate the negative impact of loss of trust due to reputation damage.

Also look at the coefficients of the time-varying branch-level control variables. Deposit growth decreases with *Deposits* and increases with *New*, consistent with the expectation that new and smaller branches may experience a higher percentage growth in deposits. Deposit growth increases with *BetterRate*, indicating that branches that offer higher deposits rates attract more deposits. We don't observe a definite relationship between the number of Google reviews and deposit growth.

Lastly, our results have demonstrated that ACC mitigates deposit outflows among branches that experienced reputation damage. However, is ACC also positively correlated with deposit growth among branches that have never been subject to reputation damage throughout our sample period? Column 5 of Table 6 shows that the coefficient estimate of ACC is not statistically or economically significant for those branches. In other words, higher level of ACC is not correlated with higher deposit growth for unshocked branches.

4.3 Sub-sample Analysis by County Characteristics

In this sub-section, we explore the heterogeneous effects of ACC across counties with different socioeconomic conditions. Specifically, we follow Equation 5 to conduct sub-sample analyses based on two crucial county-level characteristics: income per capita and population mobility.[18] Local income per capita serves as a proxy for customer wealth, while population mobility is indicative of the compositions of existing and new customers. Arguably, ACC is more likely to contribute to

[18] In order to fully control for unobservable bank-county level omitted variables, we are unable to conduct the cross-sectional analysis by including an interaction term. County-level dummy variables will be fully absorbed by high dimensional bank-county-shock year FEs.

bank resilience in low-mobility markets where there are long-standing relationships. In Panel A of Table 7, we conduct the regressions among branches that are located in counties where the income per capita is in the top 25% and bottom 25% nationally. In Panel B of Table 7, we conduct the regressions among branches that are located in counties where the population mobility is in the top 25% and bottom 25% nationally.

We find that the relationship between ACC and deposit growth is only significant in high income per capita and low mobility counties. The findings are consistent with our hypothesis that the economic value of investments into intangible assets, such as ACC, increases with customer wealth. Furthermore, given that a resilient retail banking relationship builds on retaining existing customers and/or attracting new customers, our results indicate that ACC may have a larger impact on retaining existing customers than acquiring new customers.

4.4 Sub-sample Analysis by Bank Size

We further posit that the links between branch ACC and deposit growths vary between community banks and large regional or super-regional banks. Specifically, we examine how the links between ACC and deposit growth vary among banks with domestic assets in the bottom 25% (maximum assets $0.78 billion) and those with domestic assets in the top 25% (minimum assets $3.76 billion) of all banks in a given year. In Table 8, we show that the relationship is statistically and economically strong for both small and large banks when the reputation shock is less severe, but only for small banks amid severe reputation damage (*Rep_20* and *Rep_25*). Economically, taking columns 5 and 6 as examples, a one-standard deviation increase (1.173) in branch rating is associated with an increase in deposit growth of 0.947% ($1.173 \times 0.807\% = 0.947\%$, statistically significant at the 5% level) for small banks and 0.292% ($1.173 \times 0.249\% = 0.292\%$, statistically not significant) for large banks.[19] Overall, our results suggest that ACC may be more crucial for community banks that heavily rely on relationship banking and soft information accumulated through effective interactions with local customers and businesses.

[19] Our results are also robust to alternative definitions of small banks (total assets under $1 billion) and large banks (total assets above $10 billion).

4.5 What do Customers Really Value: The Heterogeneous Effects of ACC Topics

In this sub-section, we employ the decomposed ACC on topics of *Accessibility*, *Hospitality*, *Product*, and *Facility*, and examine what aspects of the banking experiences are most likely to help branches mitigate deposit outflows in the wake of reputation shocks. We investigate this question using the following specification:

$$\begin{aligned} DepositGrowth_{i,t} = &\beta_1 TopicACC_{i,t,d} + \beta_2 NumReviews_{i,t} + \beta_3 Deposits_{i,t-1} \\ &+ \beta_4 BetterRate_{i,t-1} + \beta_5 CountyShare_{i,t-1} + \beta_6 New_{i,t-1} \\ &+ \beta_7 RateSetter_{i,t-1} + FE + \varepsilon_{i,t} \end{aligned} \tag{6}$$

where i indexes branches, d topics, and t years. The regression is performed at the branch-year level, where branches are the branch offices of banks that has experienced a reputation shock in the past 12 months (an increase in the RepRisk Index by at least 10, 15, 20, or 25) and years represent the years in which the reputation shocks occurred. $TopicACC_{i,t,d}$ is the average google rating of branch i on topic d as of year t, whose calculation is presented in Equation 2. Other variables and fixed effects are defined in the same way as those in Equation 5. Standard errors are clustered at the bank-county-shock level.

The results are presented in Table 9. To conserve space, we compress the control variables but we do present the full table in Appendix A5. We find that the coefficient on *Accessibility* is positive and statistically significant in all four specifications, while the coefficient on *Facility* is positive and statistically significant when the reputation shock is relatively weaker (*Rep*_10=1 or *Rep*_15=1). The coefficient on *Hospitality* is positive and statistically significant amid severe reputation damage (*Rep*_25=1).

The effects are also economically sizable. Take column 2 as an example: for each one standard deviation increase in *Accessibility* (0.135), the deposit growth increases by 0.457% (0.135 × 3.388% = 0.457%), equivalent to 4.86% of the mean deposit growth (9.4%); for each one standard deviation increase in *Facility* (0.082), the deposit growth increases by 0.220% (0.082 × 2.683% = 0.220%), equivalent to 2.34% of the mean deposit growth (9.4%). The coefficients on other topics are not statistically significant. Berger, Kravitz, and Shibut (2021) argue that depositors, especially the uninsured ones, are responsive to the condition of their local banks because they wish to minimize the potential for convenience losses in the event of bank failure. Our results suggest that the additional convenience offered by local branch offices, through accessible services and superior facilities, is helpful to mitigate the concerns about convenience losses and retain depositors in the wake of reputation shocks.

5 Robustness and Discussions

In this section, we discuss and extend our main results. Section 5.1 discusses a potential selection issue and address it using an alternative empirical framework. In Section 5.2, we use the most granular data to control for remaining heterogeneity across neighborhoods in the same county. Section 5.3 analyzes if deposits flow out of the local banking sector following reputation shocks. Lastly, Section 5.4 provides further robustness on the relationship between ACC and resilience of retail banking relationship, by 1) examining the other important retail banking function - mortgage lending, and 2) exploiting an alternative positive shock on business expansion instead of a negative shock on deposit retention.

5.1 A Triple Difference Approach for ACC and Deposit Growth

In Section 4.1, we utilized an event study approach to investigate whether branches with higher levels of ACC are better able to withstand negative shocks to reputation. The event study approach allows us to exploit the heterogeneous levels of ACC among branches of the same bank in the same county and investigate its impact on deposit growth. However, the bank-county-shock fixed effects require each bank to have at least two branches within a county. This can introduce a sample selection bias in that for those bank-county pairs that only have one branch, customers might have limited choices of where to move their deposits, especially if they want to move their deposits across branches within the same bank and county. In this case, the effects of ACC on deposit growth may be limited, such that our previous results may overestimate their mean effects.

In this sub-section, we use a triple difference approach to resolve the sample selection issue.

Instead of comparing the deposit growth rates between branches of the same bank, we compare branches of banks that are subject to reputation shocks with those that are not. This allows us to loosen the restrictions on the number of branches per county-bank pair, and examine the joint effect of ACC and reputation shock on deposit growth.[20] The treatment group includes all branches of banks that experienced a reputation shock in the past 12 months. For each treatment branch in each treatment year, the control branches include all branches located in the same county that did not experience any reputation shocks in the past 12 months. We consider a treatment branch and its control branches as a cohort. We estimate the joint effect of ACC and reputation shock using the following specifications:

$$\begin{aligned} DepositGrowth_{i,t} = &\beta_1 Treat_{k,t} \times Post_t \times ACC_{i,t} + \beta_2 Treat_{k,t} \times Post_t + \beta_3 Treat_{k,t} \times ACC_{i,t} \\ &+ \beta_4 Post_t \times ACC_{i,t} + \beta_5 Treat_{k,t} + \beta_6 Post_t + \beta_7 ACC_{i,t} \\ &+ \Lambda \times T_{i,t-1} + FE + \varepsilon_{i,t}, \end{aligned} \tag{7}$$

where $Treat$ is a dummy variable that is equal to one if the RepRisk Index of a bank increases by more than a threshold (10, 15, 20, or 25) over the year, and zero if the increase is less than 10. $Post$ is a dummy variable equal to one during the year of reputation shock, and zero in the prior year.[21] $T_{i,t-1}$ is a vector of control variables of branch characteristics including $NumReviews$, $Deposits$, $BetterRate$, $CountyShare$, New, and $RateSetter$. We employ the restrictive cohort fixed effects and bank-county or bank-county-year fixed effects that eliminate any unobservable determinant of deposit growth specific to branches within a cohort or a bank-county or bank-county-year cluster. The standard errors are clustered by cohort.

Appendix A6 presents the estimation results of Equation 7. In Panel A, we employ bank-county fixed effects. In Panel B, we use the more restrictive bank-county-year fixed effects, which absorb

[20] The reasons that we do not use the difference-in-differences approach in the main regression are two folds: i) It cannot effectively rule out the effects of time-varying bank-county-specific omitted variables. It is impossible to include fixed effects at the finest level given the treatment dummy is constructed at the bank-year level; ii) In counties with very few banks or are monopolized by a large bank, it can be hard to find sensible control groups that are comparable with the treatment banks. Unlike experiments that build on natural disasters where adjacent counties are sensibly considered as controls that could, but wasn't affected, identifying branches that could/should, but wasn't affected by a reputation event is extremely hard. Thus, we are just using the triple difference approach as a robustness check to our results.

[21] We require that neither the treatment nor control bank experienced any reputation shock in the control year ($Post$=0). Control banks are included in the sample with replacement.

the effects of $Post$ and $Treat \times Post$. The definition of $Treat$ is based on the threshold of 10, 15, 20, and 25 in columns (1), (2), (3), and (4), respectively. The results reconfirm our main findings in Table 5 and 6. The coefficients on $Treat \times Post$ in Panel A are negatively significant at the 1% level, suggesting a negative impact of reputation shocks on deposit growth. In the meantime, the triple interaction term $Treat \times Post \times ACC$ is positively significant at the 1% or 5% levels in both Panel A and Panel B, reconfirming that higher levels of ACC help mitigate the negative impact of reputation shocks on deposit growth. In sum, both the event study method in Section 4 and the triple difference approach in this sub-section show that ACC plays a crucial role in helping branches withstand shocks to bank reputation.

5.2 Heterogeneity in Within-county Branch Resources Allocations

The restrictive bank-county-shock fixed effects in Equation 5 preclude the impacts of any time-varying bank and county specific characteristics on deposit flows. However, even within the same county, there could still be large variations in neighborhood characteristics (e.g., customer wealth). For example, within New York County (Manhattan), the income average for the top 1% is more than 110 times that of the bottom 99%.[22] If banks allocate more internal resources to enhance the customer experience (i.e., branch ratings) of those branches in more affluent neighborhoods compared to other branches, and if this internal resource allocation is correlated with deposit growth in the wake of reputation shocks, then our results may be confounded.

Although it is difficult to fully control for all the neighborhood characteristics that can affect both deposit growth and customer experience, we try to alleviate this concern by analyzing within even more granular geographical areas. Specifically, we apply bank-ZIP Code-shock fixed effects to Equation 5. This compares the deposit flows of branches within a same bank and a same ZIP Code in the year of reputation shock. Appendix A7 reports the results. As expected, the more restrictive set of fixed effects significantly reduces the sample size, as they require a bank to have at least two branches within a same ZIP Code. The coefficients are statistically significant at the 1% to 10% levels in columns 1 to 3, and the economic magnitudes still remain sizable. While the statistical significance is much weaker in column 4, the economic magnitude remains comparable

[22] "Infographic shows New York has the highest income inequality," https://www.mytwintiers.com/news-cat/infographic-shows-new-york-has-the-highest-income-inequality/.

to earlier results in columns 1 to 3. This result indicates that our previous results in Table 6 are less likely to be confounded by geographical variations in neighborhood characteristics and internal resource allocations.

5.3 Do Deposits Flow out of the Local Banking Sector Following Reputation Shocks?

As deposits flow out of the banks that are subject to reputation shocks, it remains unknown where the deposits flow to. The depositors can either move their deposits out of the local banking sector to other markets, or within the county to neighboring or competitor banks, or both. Directly measuring the change in the deposit growth at each individual neighboring or competitor bank branch is difficult because of the possibility of multiple destinations of deposit flow. Instead, we can test whether the deposits still stay within the same county, or flow to other markets, by examining the response of county-level deposits to reputation shocks occurring on the banks in the county. If the county-level deposit growth significantly drops after reputation shocks, then it is evident that deposits flow out of the local banking sector to other markets. If there is no significant change in the county-level deposit growth, then it is more likely that deposits flow within the county to neighboring or competitor banks. We construct a set of county-year variables, $Share\_J$, to measure the share of branch deposits in a county that are subject to a jump in the RepRisk Index by more than J (J=10, 15, 20, or 25), and we run the following OLS panel regression of county-level deposit growth on these variables individually:

$$DepositGrowth_{j,t} = \beta Share\_J_{j,t} + \Lambda \times C_{j,t} + FE + \varepsilon_{j,t}, \tag{8}$$

where j indexes counties and t years. *DepositGrowth* is the county-level deposit growth. C is a vector of control variables including lagged total deposits of all bank branches in the county (*Deposits*), the number of bank branches per 1,000 population in the county (*Branch*), and the Herfindahl-Hirschmann index of deposits at all bank branches in the county (HHI). We employ county fixed effects and year fixed effects to control for any unobservable county-specific or time-specific determinants of deposit growth. Standard errors are clustered at the county level.

Appendix A8 presents the estimation results of Equation 8. We find no significant change in the county-level deposit growth following less severe reputation shocks (*Rep_10* and *Rep_15*), but observe significant outflows when the reputation damages are severe (*Rep_20* and *Rep_25*). The results suggest that depositors are likely to transfer their deposits within the county when a lower share of the county's banks are subject to reputation shocks, while they move their deposits outside the local banking sector when a significant portion of local banks are subject to reputation damage.

5.4 The Impact of ACC on Mortgage Demand

While we have shown that higher levels of ACC help retain depositors in the wake of reputation shocks, the effect of ACC on the resilience of retail banking relationships can go above and beyond depositor retention to borrower growth. In this sub-section, we examine another important retail banking product on the asset side - residential mortgage. We investigate whether higher levels of ACC help attract more mortgage businesses using natural disasters as positive shocks to local residential mortgage demand. Natural disasters can generate positive shocks to local mortgage demand because disaster-affected residents must rebuild or replace their damaged homes and businesses (Cortés and Strahan (2017)). For example, a household may take a refinancing loan which converts home equity into cash in order to pay for home repair.

We collect annual mortgage application data from the Home Mortgage Disclosure Act (HMDA) database and Presidential Disaster Declaration data from the Federal Emergency Management Agency (FEMA).[23] As the HMDA does not disclose which specific branch a mortgage application is submitted to, we collapse the Google rating data and HMDA data into bank-county-year level observations.

Our empirical design follows Dlugosz et al. (2019) and involves a triple difference approach. A county is considered a treatment county if it was hit by at least one natural disaster in a given year (treatment year) and didn't experience any disaster in the preceding year (control year). A county is considered a control county if it is located in the same state but didn't experience any disaster during the two-year window. We consider all the disasters occurred in a given state in a given year

[23]FEMA reports all natural disasters declared by the President of the United States and provides associated information including incidence dates, disaster types, and affected counties, etc. The property damages caused by the President-declared disasters are generally severe, so that they are likely to create shocks to mortgage demand.

as one disaster event, and the treatment counties and their control counties in the disaster event as a cohort.[24] We compare mortgage applications to higher-ACC banks and lower-ACC banks in treatment and control counties during the two-year event window. Specifically, we estimate the following regression:

$$
\begin{aligned}
ln(Applications)_{j,k,c,t} =& \beta_1 Treat_{j,c} \times Post_{c,t} \times HighACC_{j,k,t} + \beta_2 Treat_{j,c} \times Post_{c,t} \\
&+ \beta_3 Treat_{j,c} \times HighACC_{j,k,t} + \beta_4 Post_{c,t} \times HighACC_{j,k,t} \\
&+ \beta_5 Treat_{j,c} + \beta_6 Post_{c,t} + \beta_7 HighACC_{j,k,t} + \Lambda \times C \\
&+ FE + \varepsilon_{j,k,c,t},
\end{aligned}
\tag{9}
$$

where j indexes counties, k banks, c cohorts, and t years. $HighACC_{j,k,t}$ is a dummy variable that equals one if bank k's average Google rating in county j in year t is at the top tercile among all bank-county-year observations within the state, and zero if it is at the bottom tercile. $Treat_{j,c}$ is a dummy variable that equals one for treatment counties and zero for control counties within a cohort c. $Post_{j,c}$ is a dummy variable that equals one for the disaster incidence year and zero for the prior year within a cohort. We include a list of control variables in C to ensure that $HighACC$ captures a distinct feature of banks not subsumed by other bank or local factors. We control for bank balance sheet variables, local bank density and concentration variables, socioeconomic and demographic characteristics, as well as the one-year lagged dependent variable (see a full list of control variables in Appendix A9 and their definition in Appendix A1).

We employ several alternative fixed effects to control for unobservable factors. First, we employ disaster year-state fixed effects (cohort fixed effects), which ensure that we compare mortgage demand across banks within economically and socially similar areas and closer time windows. Second, we employ disaster year-state-bank fixed effects. This allows us to do a within-bank comparison of the mortgage demand within economically and socially similar areas and closer time windows. Third, we use bank-county fixed effects to control for any unobservable time-invariant local and bank characteristics. Finally, we add bank-county fixed effects to disaster year-state fixed effects. We cluster the standard errors at the county-bank level.

[24]The control counties are matched with treatment counties with replacement. For example, for a control county, a same county-year observation can show up in one cohort as a treatment year observation, and show up again in another cohort as a control year observation.

Appendix A2 reports the summary statistics for the Google rating-FEMA-HMDA-merged sample. Panel A shows the frequency of natural disasters and the number of affected counties. Our sample includes 138 unique natural disasters and 1,485 affected counties. On average, 10.76 counties were hit by each disaster. The three most frequent types of disaster are severe storms, floods, and hurricanes, followed by snow and tornado. Panel B shows that for all banks in our sample, 24.8% of them have an ACC that is at the top tercile in its state, while 75.2% are in the bottom tercile. The average number of reviews for an average bank in an average county in a given year is 8.120. The annual number of mortgage applications for an average bank in an average county is 82 applications.

Table 10 reports the results of Equation 9. We compress the control variables to conserve space, and show the complete table in Appendix A9. The results show that mortgage demand increases following natural disasters. The coefficient on $Treat \times Post$ is positive and statistically significant at the 1% level and is robust across alternative choices of fixed effects. Economically, taking column 1 as an example, the number of applications surged by 35.5% for lower-rated banks in treatment counties. This result validates the premise of using natural disasters as demand shocks. We also find that following natural disasters, the increase in loan applications to highly-rated banks is higher than that to lower-rated banks. The coefficient on $Treat \times Post \times HighACC$ is positive and statistically significant at the 1% or 5% level and is robust across alternative fixed effects. The estimate is also economically significant. Taking column 1 as an example, the increase in the number of applications to highly-rated banks exceeded that to lower-rated banks by 20.3%. In sum, the results in Table 10 suggest that in cases of demand shocks, mortgage borrowers strongly prefer those branches with higher customer satisfaction to seek funding.[25]

We then investigate what aspects of branch services are more crucial to mortgage borrowers' choices of lending bank, we utilize the topic-specific ACC measures as defined in Equation 3 to explain borrowers' mortgage applications to each bank after natural disasters. To allow easier

[25] A concern about our result could be that it is driven by households who seek to refinance their mortgages after natural disasters. They may just go to their original bank with whom they have an existing mortgage lending relationship, instead of going to a high ACC bank for financing. Since those highly-rated banks originally had more mortgage businesses (the significant coefficient on the stand-alone term $HighACC$ in Table 10), the coefficient on the triple-interaction term may just reflect those returning households who originally had mortgage contracts with the bank. To alleviate the concern, we re-estimate Equation 9 separately on new purchases loans and refinance loans, because new home purchase borrowers are less likely to be returning customers. We report the results in Appendix A11. Our results are robust to the choices of different loan purposes.

interpretation of the triple difference results, we construct a $HighTopicACC$ dummy that equals one if a banks average Google rating in a given county in a given year on given topic is at the top tercile among all bank-county-year observations of that topic in the state, and zero if it is at the bottom tercile. Then, we estimate a similar difference-in-differences regression as Equation 9 but replace $HighACC$ with $HighTopicACC$.

Appendix A10 presents the results. We find that loan demand is higher for banks who have higher levels of ACCs on hospitality and facility. The coefficients on the triple interaction term are statistically significant at the 1% level for hospitality and facility. The economic magnitude is also sizeable. Taking column 6 as an example, the increase in the number of applications to banks with high hospitality rating exceeded low hospitality rating banks by 33.9%. Similarly, taking column 8, the increase in the number of applications to banks with high facility rating exceeded that to low facility rating banks by 38.3%. The results indicate that human interactions with branch employees and facilities of the branch are crucial criteria for borrowing when they are choosing the lending bank. We also find that the role of accessibility and product are less significant. The coefficient on the triple interaction term for accessibility and product is still positive, but less significant statistically (significant at the 5% or 10% levels) and economically. The results in Appendix A10 indicate that human interactions and bank facility play crucial roles in affecting the decisions of mortgage borrowers in the wake of natural disasters. Banks with better customer interactions and facilities gain popularity because they better resisted the disasters and responded to customers' urgent needs in the face of disasters.[26]

6 Conclusion

This paper provides a detailed framework to quantify the accumulated customer capital (ACC), and examine the relationship between this important intangible assets and bank resilience. We use Google ratings to measure the customers' perception of a branch's services and products, and exploit machine learning techniques to capture the key determinants of ACC from the information embedded in the specific comments that accompany these ratings. We find that branch-level ACCs

[26] Indeed, following natural disasters, banking regulators (e.g., the Federal Reserve and FDIC) usually expedite any request to operate temporary banking facilities to provide more convenient availability of services to affected borrowers.

are correlated with a number of factors related to bank size, organizational structure, and pricing behavior. We also find that while branch ACCs are generally stationary over time, there are considerable variations in ACCs among branches operated by the same bank in a given county.

The key question that we explore is whether branches with higher levels of ACC are better able to withstand exogenous demand shocks as captured by the RepRisk database. While we find strong evidence that there is a significant decline in deposit growth in the aftermath of these negative reputation shocks, we show that the branches with higher levels of ACC are significantly better at mitigating the impact of these shocks. Overall, these results provide compelling evidence that banks with stronger ACC have more resilient retail relationships. We also find that the resilience of retail relationships is greater in areas with higher income levels and lower population mobility. Notably, we also find that intangible customer capital is more important for smaller community-oriented banks than they are for branches of larger bank holding companies.

Taking a closer look at the specific customer comments, we consider four key dimensions influencing ACC: 1) accessibility of the services, 2) hospitality of the staff, 3) the quality of the products, and 4) quality of the facilities. We find that the accessibility dimension is the key factor driving depositor retention.

Altogether, our results provide compelling evidence that the existence and resilience of retail banking relationships are significantly driven by intangible customer capital. These findings confirm the value of the continued role of community-oriented banking despite the ongoing consolidation within the industry, and provides an interesting backdrop to consider the impact of continued technological changes that have dramatically transformed the various ways in which banks interact with their customers.

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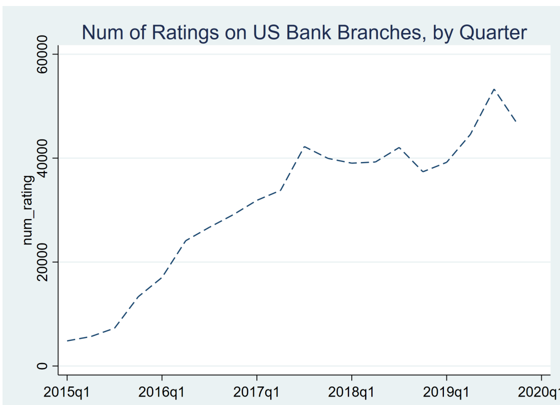
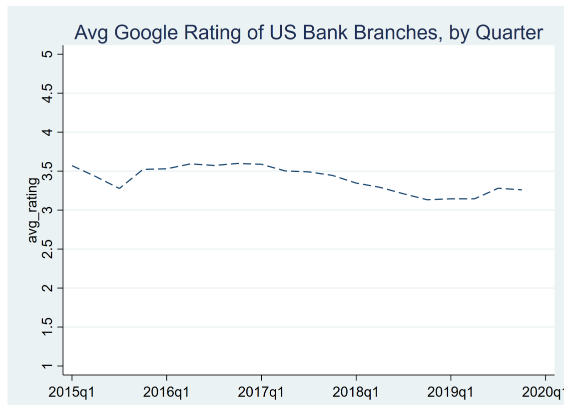
Figure 1. Number and Average Scores of Google Rating by Quarter

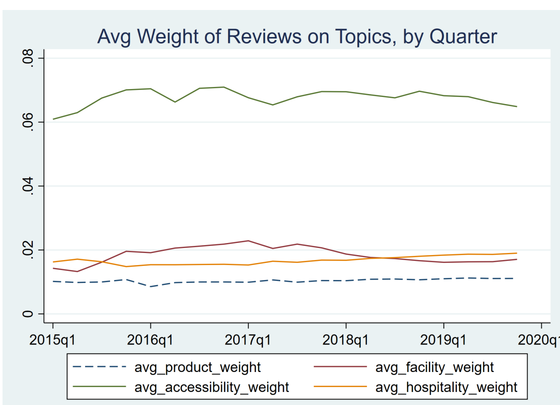
The following figures summarize Google ratings by quarter from 2015 to 2019. Figure 1A reports the number of new Google reviews on U.S. bank branches in each quarter. Figure 1B reports the average Google rating score of U.S. bank branches by quarter. Figure 1C reports the average weight (frequency of mentions of topic-specific words over the length of the review) of reviews for four topics: product, facility, accessibility, and hospitality. Figure 1D reports the average rating score by topics.



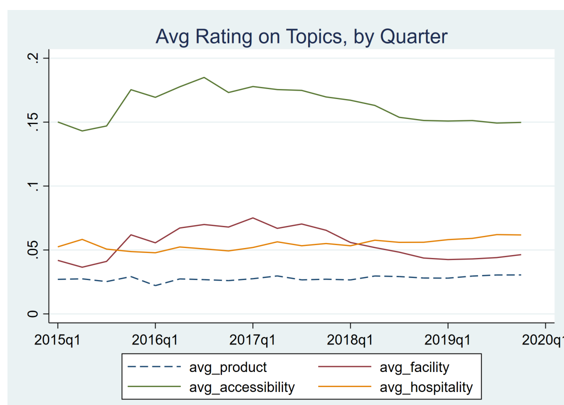
Panel A



Panel B



Panel C



Panel D

Figure 2. The Monthly Change in RepRisk Index, Wells Fargo

The following figure reports the monthly change in the RepRisk Index of Wells Fargo. The blue boxes represent the important media exposures and key incidents along the timeline of Wells Fargo's recent scandal.

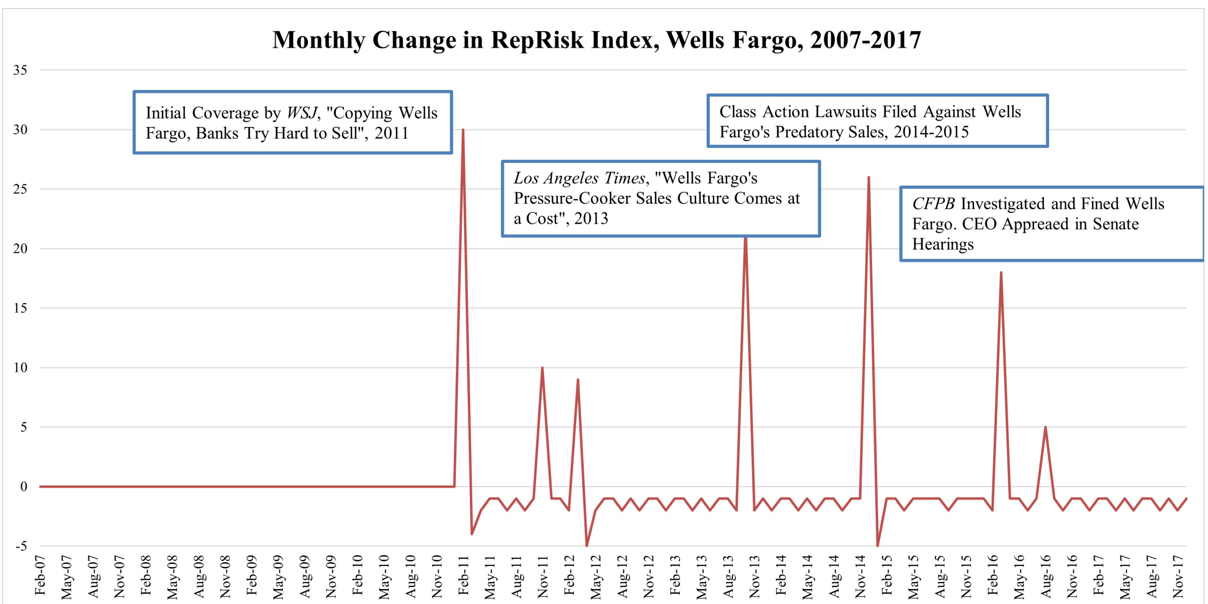
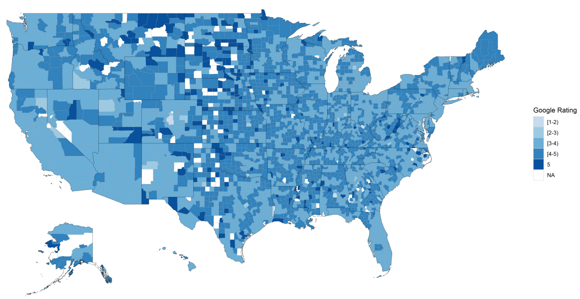
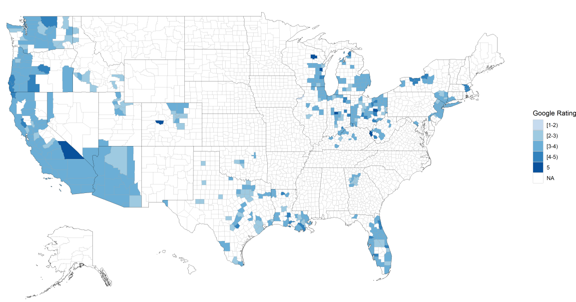


Figure 3. Average ACC by County

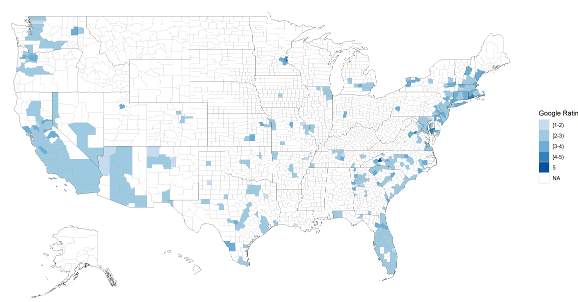
These figures show the county-level average ACC for branches of all banks (Figure 3A), branches of JPMorgan Chase Bank, N.A. (Figure 3B), and branches of Bank of America, N.A. (Figure 3C), as observed on December 31, 2019.



Panel A All Banks



Panel B JPMorgan Chase Bank, N.A.



Panel C Bank of America, N.A.

Figure 4. Effects of Reputation Shocks and Deposit Growth

This figure reports the coefficient estimates and the corresponding 95% confidence intervals of panel OLS regressions of branch deposit growth on the reputation shock dummies.

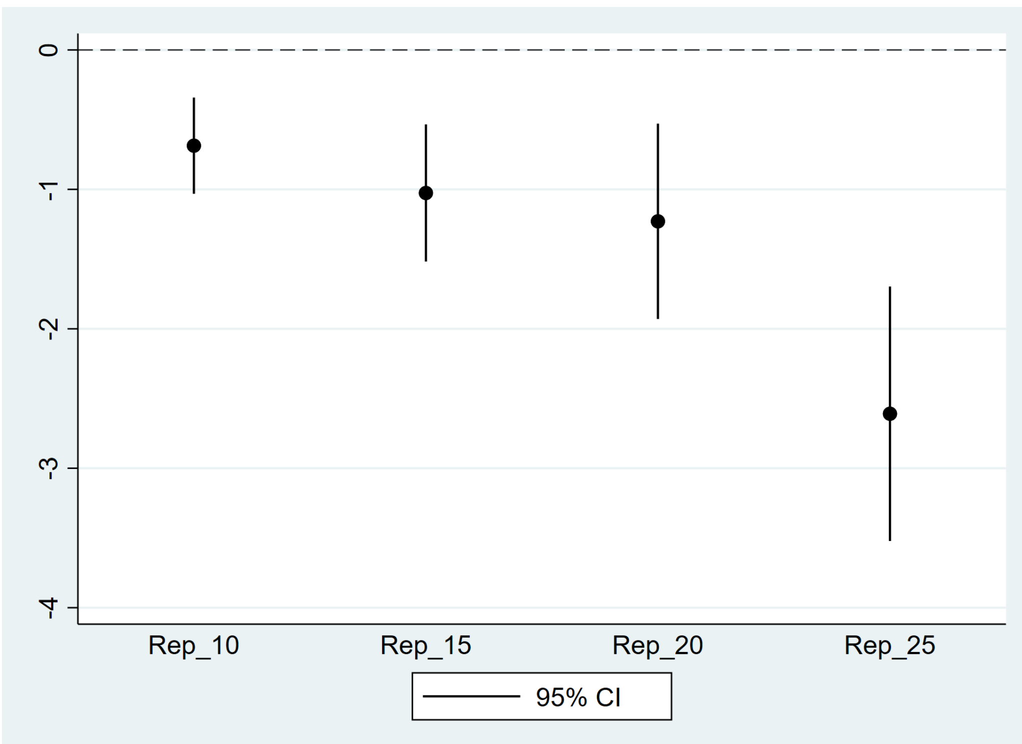


Table 1. Summary Statistics
This table reports the summary of statistics for the key variables in the Call Report-SOD-RateWatch-RepRisk-merged sample, from 2015-2018. ACC and other variables obtained from Google Map Cloud are only reported for those branches with non-missing Google Profiles as of every mid-year.

	N	Mean	Median	S.D.
Branch Characteristics				
DepositGrowth (%)	135,834	9.404	5.989	21.171
Deposits ($Mil)	135,834	91.705	60.374	120.207
BetterRate	135,834	0.688	1.000	0.463
Samestate	135,834	0.205	0.000	0.404
New	135,834	0.009	0.000	0.094
RateSetter	135,834	0.027	0.000	0.161
Reputation Shocks				
Rep_10	135,834	0.550	1.000	0.497
Rep_15	98,785	0.382	0.000	0.486
Rep_20	81,092	0.247	0.000	0.431
Rep_25	75,121	0.187	0.000	0.390
Rep_Chg	135,834	11.888	11.000	8.904
Bank Characteristics				
Loan	135,834	0.562	0.593	0.153
ROA	135,834	0.005	0.005	0.003
Liquidity	135,834	0.085	0.062	0.099
Sensitivity	135,834	-0.095	-0.108	0.109
CountyShare	135,834	0.039	0.007	0.096
County Characteristics				
Income	135,830	32.536	30.732	8.848
Mobility	135,822	110.542	105.234	37.436
ACC and Google Cloud				
ACC	88,845	3.538	3.667	1.173
NumReviews	88,845	4.859	3.000	5.226
Accessibility	88,845	-0.020	0.000	0.135
Hospitality	88,845	0.005	0.000	0.061
Product	88,845	-0.005	0.000	0.050
Facility	88,845	0.003	0.000	0.082

Table 2. Variance Decomposition Analysis

This table examines how bank branches' ACCs are explained by a variety of fixed effects. Panel A reports the results on the cross-sectional regressions of ACCs as of December 31, 2019 on a variety of fixed effects. Panel B reports the results on the panel regressions of ACCs on a variety of fixed effects using a sample consisting of all branch-years with non-missing Google Profiles from 2015 to 2019. Adjusted R^2s are reported for each model.

Panel A - Cross-sectional

	ACC		
	(1)	(2)	(3)
Bank FE	+		
County FE		+	
Bank × County FE			+
Observations	73,941	74,906	63,844
Adjusted R^2	0.227	0.090	0.296

Panel B - Panel

	ACC							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Bank FE	+							
County FE		+						
Branch FE			+				+	+
Year × Bank FE				+		+	+	
Year × County FE					+	+	+	
Year × Bank × County FE								+
Observations	188,234	189,264	153,099	188,095	187,032	185,641	150,183	138,975
Adjusted R^2	0.101	0.054	0.617	0.112	0.053	0.136	0.633	0.627

Table 3. Determinants of Branch-level ACCs

This table reports the deterministic regression of ACCs. In columns 1 and 2, the dependent variable is the ACC of each bank branch observed on December 31, 2019. The independent variables consist of bank and branch level characteristics in 2019. Bank characteristics include *Small* and *Local* dummies. *Small* equals one if a bank has less than two billion in assets. *Local* equals one if a bank obtains more than 65% of its deposits from a single county. Branch characteristics include *CountyShare*, *RateSetter*, *BetterRate*, *SameState*, and *New*. *CountyShare* is the branch's market share of deposit in the county. *RateSetter* equals one if the branch is rate-setting branch. *BetterRate* equals one if the average rate of 12-month CD products is higher than the county median. *SameState* equals one if a branch is in the same state with the headquarter of the bank. *New* equals one if a branch was established within the past five years. In columns 3 and 4, we perform a similar analysis using the sample consisting of all branch-years with non-missing Google review information from 2015 to 2019. Standard errors are clustered at the county level in columns 1 and 2, and at the county-year level in columns 3 and 4. T-statistics are shown in parentheses. Statistical significance at the 10%, 5% and 1% levels is denoted by *, ** and ***, respectively.

	ACC			
	Cross-sectional		Panel	
	(1)	(2)	(3)	(4)
Small	0.463***	0.268***	0.442***	0.298***
	(29.15)	(14.76)	(28.71)	(17.65)
Local	0.214***	0.124***	0.204***	0.126***
	(10.46)	(6.55)	(10.19)	(6.57)
CountyShare		-0.831***		-0.676***
		(-9.57)		(-12.86)
RateSetter		-0.00544		-0.0210*
		(-0.33)		(-1.69)
BetterRate		0.189***		0.112***
		(11.64)		(10.77)
SameState		0.254***		0.209***
		(15.79)		(17.91)
New		0.255***		0.268***
		(13.08)		(19.93)
County FE	+	+		
County × Year FE			+	+
Observations	67,986	64,905	179,705	176,624
Adjusted R^2	0.128	0.151	0.061	0.071

Table 4. Branch-level ACCs and Customer Sentiment

This table reports how branch-level ACCs are correlated with the textual metrics of sentiments and emotions. The dependent variable is the branch-level ACC observed as of December 31, 2019. The independent variables are the weights of words associated with each sentiment and emotion in all of the branch's reviews (i.e., frequency of mentions over the total length of the reviews). Standard errors are clustered at the county level and t-statistics are shown in parentheses. Statistical significance at the 10%, 5% and 1% levels is denoted by *, ** and ***, respectively.

	ACC	
	(1)	(2)
Positive	2.584***	
	(15.24)	
Negative	-5.516***	
	(-19.78)	
Trust		0.824***
		(5.88)
Sadness		-0.838***
		(-2.60)
Surprise		-0.236***
		(-2.65)
Joy		2.387***
		(14.63)
Disgust		-0.292
		(-0.78)
Fear		-1.489***
		(-3.79)
Anger		-4.125***
		(-14.36)
Anticipation		-1.452***
		(-6.48)
County FE	+	+
Observations	67,481	67,481
Adjusted R^2	0.259	0.232

Table 5. Reputation Shock and Deposit Growth

This table reports the results on the OLS regressions of branch deposit growth on the bank's reputation shock proxies. *DepositGrowth* is the annual growth in branch deposits. *Rep_J* is a dummy variable that turn on if the RepRisk Index jumps more than J (J= 10, 15, 20, or 25) over the past year, and zero if the jump is less than 10. *Rep_Chg* is the bank's maximum jump in RepRisk Index over the past year. *Deposits* is the amount of branch deposits. *BetterRate* is a dummy variable that equals one if the average rate of 12-month CD products at the branch is higher than the county median, and zero otherwise. *CountyShare* is the market share of the branch in the county by deposits. *Loan* is the share of loans in total assets. *ROA* is the bank's return on assets. *Liquidity* is cash divided by total deposits. *Sensitivity* is the sensitivity to interest rate risk. Standard errors are clustered at the branch level and t-statistics are shown in parentheses. Statistical significance at the 10%, 5% and 1% levels is denoted by *, ** and ***, respectively.

	DepositGrowth				
	(1)	(2)	(3)	(4)	(5)
Rep_10	-0.687***				
	(-3.90)				
Rep_15		-1.026***			
		(-4.09)			
Rep_20			-1.229***		
			(-3.44)		
Rep_25				-2.609***	
				(-5.60)	
Rep_Chg					-0.034***
					(-3.72)
Deposits	-0.152***	-0.175***	-0.177***	-0.172***	-0.152***
	(-12.34)	(-13.13)	(-11.64)	(-10.50)	(-12.34)
BetterRate	0.015	1.271**	1.896***	2.064***	-0.048
	(0.04)	(2.54)	(2.68)	(2.61)	(-0.13)
CountyShare	-225.506***	-200.464***	-229.612***	-226.832***	-225.369***
	(-14.95)	(-12.77)	(-13.23)	(-12.00)	(-14.93)
Loan	3.893***	4.174***	6.015***	6.979***	4.433***
	(3.79)	(2.97)	(3.05)	(3.36)	(4.27)
ROA	34.706	65.075**	39.148	96.593*	40.329
	(1.32)	(2.10)	(0.87)	(1.96)	(1.52)
Liquidity	2.543*	2.076	8.875**	13.498***	3.523**
	(1.78)	(0.73)	(2.18)	(2.99)	(2.51)
Sensitivity	5.637***	4.772***	8.743***	11.809***	5.774***
	(4.41)	(3.34)	(4.49)	(5.15)	(4.52)
Branch FE	+	+	+	+	+
County $\times$ Year FE	+	+	+	+	+
Observations	135,834	93,510	70,696	63,829	135,834
Adjusted R^2	0.157	0.127	0.106	0.109	0.157

Table 6. Reputation Shock, ACC, and Deposit Growth

This table reports the OLS regression of branch deposit growth on the branch-level ACC for banks that experienced reputation shocks. The observations are at the branch-year level, where branches are the branch offices of banks that experienced a reputation shock in the past 12 months (an increase in RepRisk index of at least 10, 15, 20, or 25 corresponds to columns 1 to 4, respectively) and years are the years of reputation shocks. *DepositGrowth* is the annual growth in branch deposits. *ACC* is the average Google rating of all the existing Google reviews on the branch. *NumReviews* is the number of Google ratings. *Deposits* is the amount of branch deposits. *BetterRate* is a dummy variable that equals one if the average rate of 12-month CD products is higher than the county median, and zero otherwise. *CountyShare* is the market share of the branch in the county by deposits. *New* is a dummy variable that equals one if a branch was established within the past five years, and zero otherwise. *RateSetter* is a dummy variable that equals one if a branch is a local rate setter, and zero otherwise. In column 5, we repeat the analysis in columns 1 to 4 using the sample consisting of branches that have never been subject to reputation shocks. Standard errors are clustered at the bank-county-shock year level and t-statistics are shown in parentheses. Statistical significance at the 10%, 5% and 1% levels is denoted by *, ** and ***, respectively.

	DepositGrowth				
	Rep_10=1	Rep_15=1	Rep_20=1	Rep_25=1	Unshocked
	(1)	(2)	(3)	(4)	(5)
ACC	0.292***	0.403***	0.375**	0.363	0.311
	(3.62)	(3.56)	(2.00)	(1.60)	(1.08)
NumReviews	0.040**	0.040	-0.052	-0.159	-0.044
	(2.15)	(1.14)	(-0.55)	(-1.44)	(-0.56)
Deposits	-0.018***	-0.013***	-0.008***	-0.004	-0.035***
	(-17.38)	(-7.91)	(-2.59)	(-1.04)	(-5.99)
BetterRate	6.429***	7.867***	17.234***	16.492***	5.501
	(4.10)	(3.11)	(4.41)	(3.84)	(1.51)
CountyShare	-16.139***	-20.070***	-25.413***	-24.861**	-4.359
	(-4.54)	(-3.95)	(-2.65)	(-2.11)	(-0.44)
New	33.095***	30.419***	40.340***	41.987***	17.991***
	(19.42)	(10.48)	(8.73)	(8.30)	(4.40)
RateSetter	-17.783***	-13.800***	-11.958***	-14.771***	0.834
	(-12.83)	(-7.42)	(-4.37)	(-4.45)	(0.34)
Bank × County × Shock FE	+	+	+	+	+
Observations	62,128	28,380	11,628	8,021	8,151
Adjusted R^2	0.153	0.128	0.152	0.168	0.162

Table 7. Cross-Sectional Analysis by County Income and Mobility

This table reports the sub-sample OLS regression of branch deposit growth on the branch-level ACC for banks that experienced reputation shocks. The observations are on the branch-year level. In Panel A, we conduct the regressions among branches that are located in counties whose income per capita are in the top 25% and bottom 25% nationally. In Panel B, we conduct the regressions among branches that are located in counties whose population mobility are in the top 25% and bottom 25% nationally. *DepositGrowth* is the annual growth in branch deposits. *ACC* is the average Google rating of all the existing Google reviews on the branch. *NumReviews* is the number of Google ratings. *Deposits* is the amount of branch deposits. *BetterRate* is a dummy variable that equals one if the average rate of 12-month CD products is higher than the county median, and zero otherwise. *CountyShare* is the market share of the branch in the county by deposits. *New* is a dummy variable that equals one if a branch was established within the past five years, and zero otherwise. *RateSetter* is a dummy variable that equals one if a branch is a local rate setter, and zero otherwise. Standard errors are clustered at the bank-county-shock year level and t-statistics are shown in parentheses. Statistical significance at the 10%, 5% and 1% levels is denoted by *, ** and ***, respectively.

Panel A: Income Per Capita

	DepositGrowth							
	Rep_10=1		Rep_15=1		Rep_20=1		Rep_25=1	
	Bottom25%	Top25%	Bottom25%	Top25%	Bottom25%	Top25%	Bottom25%	Top25%
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ACC	0.185	0.350**	0.088	0.789***	-0.027	0.793**	-0.104	0.852**
	(1.16)	(2.33)	(0.41)	(3.49)	(-0.08)	(2.05)	(-0.24)	(1.98)
NumReviews	0.049	0.070**	-0.013	0.090**	-0.070	-0.075	-0.032	-0.139
	(1.20)	(2.38)	(-0.17)	(1.97)	(-0.38)	(-0.51)	(-0.16)	(-0.56)
Deposits	-0.016***	-0.019***	-0.009**	-0.015***	-0.005	-0.006	0.008	-0.003
	(-6.59)	(-10.65)	(-2.24)	(-5.00)	(-0.63)	(-0.87)	(0.88)	(-0.34)
BetterRate	6.913***	-0.476	7.497*	-1.639	15.927**	11.301*	12.672**	10.092
	(2.62)	(-0.17)	(1.74)	(-0.35)	(2.08)	(1.82)	(1.99)	(1.43)
CountyShare	-20.299***	-20.363*	-22.773***	-17.459	-28.429**	-63.858	-36.501**	-79.671
	(-4.23)	(-1.86)	(-2.95)	(-1.20)	(-2.04)	(-0.84)	(-2.04)	(-0.83)
New	24.726***	39.228***	25.700***	34.400***	37.941***	40.156***	34.010***	45.690***
	(7.08)	(12.45)	(4.21)	(6.22)	(4.20)	(4.37)	(3.39)	(4.25)
RateSetter	-7.595***	-29.283***	-7.945**	-26.023***	-9.593**	-25.501***	-8.213*	-31.168***
	(-3.25)	(-10.13)	(-2.55)	(-5.83)	(-2.38)	(-3.68)	(-1.88)	(-3.60)
Bank × County × Shock FE	+	+	+	+	+	+	+	+
Observations	13,876	16,336	6,174	7,512	2,514	3,021	1,743	2,124
Adjusted R^2	0.127	0.190	0.096	0.165	0.090	0.172	0.128	0.176

Panel B: Mobility

	DepositGrowth							
	Rep_10=1		Rep_15=1		Rep_20=1		Rep_25=1	
	Bottom25%	Top25%	Bottom25%	Top25%	Bottom25%	Top25%	Bottom25%	Top25%
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ACC	0.408**	0.023	0.370*	0.175	0.597*	0.216	0.604	0.337
	(2.29)	(0.15)	(1.70)	(0.71)	(1.68)	(0.63)	(1.47)	(0.79)
NumReviews	0.015	0.033	0.013	0.035	0.002	-0.012	-0.119	-0.004
	(0.40)	(1.04)	(0.18)	(0.57)	(0.01)	(-0.06)	(-0.77)	(-0.01)
Deposits	-0.021***	-0.020***	-0.015***	-0.014***	-0.011***	-0.005	-0.010*	-0.008
	(-10.49)	(-8.65)	(-4.97)	(-3.65)	(-2.88)	(-0.68)	(-1.86)	(-0.71)
BetterRate	3.476	2.569	7.669*	4.052	13.053*	14.286*	12.331	14.486*
	(1.26)	(0.99)	(1.75)	(1.01)	(1.65)	(1.95)	(1.58)	(1.74)
CountyShare	-20.466	-15.579***	-30.024	-20.733***	-20.736	-17.941	-21.099	-5.025
	(-1.21)	(-3.10)	(-1.61)	(-2.89)	(-1.10)	(-0.91)	(-0.78)	(-0.22)
New	40.734***	30.474***	40.362***	29.114***	51.463***	40.742***	50.350***	43.978***
	(10.39)	(8.93)	(6.16)	(5.23)	(4.85)	(4.46)	(4.21)	(4.36)
RateSetter	-27.732***	-16.464***	-23.423***	-13.581***	-23.652***	-13.153***	-28.799***	-16.667***
	(-7.54)	(-6.61)	(-4.94)	(-4.07)	(-3.19)	(-2.67)	(-3.07)	(-2.75)
Bank × County × Shock FE	+	+	+	+	+	+	+	+
Observations	16,300	14,593	7,514	6,592	3,166	2,656	2,210	1,858
Adjusted R^2	0.149	0.147	0.134	0.126	0.155	0.178	0.163	0.188

Table 8. Cross-Sectional Analysis by Bank Size

This table reports the OLS sub-sample regression of branch deposit growth on the branch-level ACC for banks that experienced reputation shocks. The observations are on the branch-year level, where branches are the branch offices of banks that experienced a reputation shock in the past 12 months (an increase in RepRisk index of at least 10, 15, 20, or 25 respectively) and years are the years of reputation shocks. We report the results using the sub-sample banks with domestic assets in the bottom 25% (maximum assets $0.78 billion) and those with domestic assets in the top 25% (minimum assets $3.76 billion) among all banks each year. *DepositGrowth* is the annual growth in branch deposits. *ACC* is the average Google rating of all the existing Google reviews on the branch. *NumReviews* is the number of Google ratings. *Deposits* is the amount of branch deposits. *BetterRate* is a dummy variable that equals one if the average rate of 12-month CD products is higher than the county median, and zero otherwise. *CountyShare* is the market share of the branch in the county by deposits. *New* is a dummy variable that equals one if a branch was established within the past five years, and zero otherwise. *RateSetter* is a dummy variable that equals one if a branch is a local rate setter, and zero otherwise. Standard errors are clustered at the bank-county-shock year level and t-statistics are shown in parentheses. Statistical significance at the 10%, 5% and 1% levels is denoted by *, ** and ***, respectively.

	DepositGrowth							
	Rep_10=1		Rep_15=1		Rep_20=1		Rep_25=1	
	Bottom25%	Top25%	Bottom25%	Top25%	Bottom25%	Top25%	Bottom25%	Top25%
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ACC	0.317***	0.263**	0.447***	0.398*	0.807**	0.249	0.649	0.216
	(2.67)	(2.16)	(2.84)	(1.95)	(2.08)	(0.81)	(1.59)	(0.51)
NumReviews	0.092	0.028	0.162	0.012	0.356	-0.142*	-0.306	-0.269**
	(1.31)	(1.46)	(1.64)	(0.33)	(0.59)	(-1.74)	(-1.01)	(-2.04)
Deposits	-0.012***	-0.021***	-0.004	-0.019***	0.022**	-0.012***	0.031***	-0.010**
	(-5.05)	(-17.92)	(-1.27)	(-9.00)	(2.29)	(-3.78)	(2.90)	(-2.36)
BetterRate	8.954**	4.590**	5.655	8.644***	25.852	19.291***	19.545	19.718***
	(2.48)	(2.32)	(0.87)	(2.74)	(1.65)	(3.76)	(1.39)	(3.56)
CountyShare	-15.247**	-16.823***	-15.325	-23.918***	74.589	-46.385***	82.825	-57.975***
	(-2.05)	(-3.95)	(-1.26)	(-3.68)	(1.56)	(-2.83)	(1.52)	(-2.85)
New	40.285***	31.432***	42.178***	27.133***	71.101***	41.832***	79.826***	42.809***
	(8.06)	(16.66)	(5.27)	(8.34)	(3.14)	(8.02)	(3.32)	(7.63)
RateSetter	-19.831***	-17.764***	-22.185***	-11.656***	-28.266	-9.434***	-46.113**	-11.205**
	(-5.47)	(-10.98)	(-4.42)	(-5.27)	(-1.50)	(-2.61)	(-2.35)	(-2.47)
Bank × County × Shock FE	+	+	+	+	+	+	+	+
Observations	18,230	38,711	10,262	14,146	2,653	5,344	2,355	3,058
Adjusted R^2	0.126	0.160	0.116	0.117	0.127	0.173	0.137	0.204

Table 9. The Differential Impacts of Decomposed Topic ACC amid Reputation Shocks This table reports the effects of topic ACC on deposit growth. The independent variable (*Accessibility*, *Product*, *Hospitality*, *Facility*) is the average topic rating on the branch up to the current year, where topic rating is defined as the relative word mentioning on a topic (frequency of key words associated with a specific topic scaled by the total number of words in the review) times the rating of the review (scaled between -2 to +2). The key words for topics are listed in Appendix A3. Columns (1) to (4) correspond to banks that experienced a reputation shock (an increase in RepRisk index of 10, 15, 20, and 25, respectively, since last June) and years of reputation shocks. Control variables include *NumReviews*, *Lag Log Deposits*, *Lag BetterRate*, *Lag CountyShare*, *New*, and *RateSetter*. Standard errors are clustered at the bank-county-shock year level and t-statistics are shown in parentheses. Statistical significance at the 10%, 5% and 1% levels is denoted by *, ** and ***, respectively.

Panel A

	DepositGrowth			
	Rep_10=1	Rep_15=1	Rep_20=1	Rep_25=1
	(1)	(2)	(3)	(4)
Accessibility	2.054***	3.388***	3.758**	4.268**
	(3.03)	(3.53)	(2.38)	(2.32)
Controls	+	+	+	+
Bank × County × Shock FE	+	+	+	+
Observations	62,128	28,380	11,628	8,021
Adjusted R^2	0.153	0.128	0.152	0.168

Panel B

	DepositGrowth			
	Rep_10=1	Rep_15=1	Rep_20=1	Rep_25=1
	(1)	(2)	(3)	(4)
Hospitality	1.622	1.806	5.785	9.480*
	(1.11)	(0.87)	(1.42)	(1.92)
Controls	+	+	+	+
Bank × County × Shock FE	+	+	+	+
Observations	62,128	28,380	11,628	8,021
Adjusted R^2	0.153	0.127	0.152	0.168

Panel C

	DepositGrowth			
	Rep_10=1	Rep_15=1	Rep_20=1	Rep_25=1
	(1)	(2)	(3)	(4)
Product	1.436	-0.508	-3.237	-4.947
	(0.74)	(-0.18)	(-0.75)	(-0.76)
Controls	+	+	+	+
Bank × County × Shock FE	+	+	+	+
Observations	62,128	28,380	11,628	8,021
Adjusted R^2	0.153	0.127	0.152	0.167

Panel D

	DepositGrowth			
	Rep_10=1	Rep_15=1	Rep_20=1	Rep_25=1
	(1)	(2)	(3)	(4)
Facility	1.792*	2.683*	2.786	2.109
	(1.74)	(1.70)	(1.20)	(0.74)
Controls	+	+	+	+
Bank × County × Shock FE	+	+	+	+
Observations	62,128	28,380	11,628	8,021
Adjusted R^2	0.153	0.127	0.152	0.167

Table 10. ACC and Mortgage Demand During Natural Disasters

This table reports the results on the triple difference regressions of mortgage applications around natural disasters. *Treat* is a dummy variable that equals one for the disaster affected counties, and zero for control counties. *Post* is a dummy variable that equals one for the disaster incidence year, and zero for the preceding year. *HighACC* is a bank-county-year-level dummy variable that equals one if the bank's average Google rating in the county is at the top tercile among all banks within the same state, and zero if it is at the bottom tercile. *ln(Applications)* is the natural logarithm of the annual number of mortgage applications to the bank in the a county. Control variables include *lag ln(Applications)*, *ln(Loan)*, *ROA*, *Liquidity*, *Sensitivity*, *Missing*, *Small*, *Local*, *Important*, *Branch*, *Deposit per Capita*, *Unemployment*, *Population*, *White*, *Female*, *Education*, *Income*, *Senior*, *Manufacturing Labor*, *Information Labor*. Standard errors are clustered at the county-bank level and t-statistics are shown in parentheses. Statistical significance at the 10%, 5% and 1% levels is denoted by *, ** and ***, respectively.

	ln(Applications)			
	(1)	(2)	(3)	(4)
Treat × Post × HighACC	0.203***	0.199***	0.149**	0.184***
	(3.57)	(3.15)	(2.53)	(3.05)
Treat × Post	0.355***	0.343***	0.246***	0.269***
	(13.43)	(11.95)	(9.79)	(10.82)
Treat × HighACC	-0.196***	-0.176***	-0.243***	-0.200***
	(-5.43)	(-4.17)	(-5.42)	(-4.14)
Post × HighACC	-0.722***	-0.756***	-0.568***	-0.710***
	(-20.96)	(-19.70)	(-17.26)	(-20.42)
Treat	-0.150***	-0.147***	0.038*	-0.131***
	(-9.72)	(-8.90)	(1.66)	(-5.23)
Post	-0.849***	-0.899***	-0.271***	-0.668***
	(-48.98)	(-45.42)	(-18.23)	(-31.04)
HighACC	0.621***	0.649***	0.720***	0.778***
	(26.75)	(23.86)	(23.09)	(23.97)
Controls	+	+	+	+
Disaster Year × State FE	+			+
Disaster Year × State × Bank FE		+		
Bank × County FE			+	+
Observations	37,173	37,170	37,170	37,170
Adjusted R^2	0.691	0.690	0.606	0.655

Appendix

Table A1. Variable Definitions

Variable	Definition	Source
Google Rating		
ACC	Branch-level cumulative average Google rating.	Google Cloud
HighACC	A dummy variable that equals one if the bank-county-year average Google rating belongs to the top tercile among all bank-county observations in the state in the year, and zero if it belongs to the bottom tercile.	Google Cloud
HighTopicACC	A dummy variable that equals one if the bank-county-year average Google rating on a specific topic (weight of words mentioning times rating of the review) belongs to the top tercile among all bank-county observations in the state in the year, and zero if it belongs to the bottom tercile.	Google Cloud
NumReviews	Cumulative number of Google ratings.	Google Cloud
Missing	A bank-county-year level dummy variable that equals one if a bank has at least one branch with missing Google rating in a year, and zero otherwise.	Google Cloud
ReputationShock		
Rep_J	A dummy variable that equals one if the bank has an increase in the RepRisk Index by at least J (J=10, 15, 20, or 25) in the past 12 months, and zero if the increase is below 10.	RepRisk
Share_J	The share of a county's bank deposits that is subject to an increase in the RepRisk Index by more than J (J=10, 15, 20, or 25).	SOD, RepRisk
Branch Characteristics		
Deposits	Branch deposits.	SOD
DepositGrowth	The annual growth in deposits at the branch or county.	SOD
CountyShare	The market share of the branch in the county by deposits.	SOD
BetterRate	A dummy variable that equals one if the average rate of 12-month CD products at the branch is higher than the county median, and zero otherwise.	RateWatch
RateSetter	A dummy variable that equals one if a branch is a local rate setter, and zero otherwise.	RateWatch
Samestate	A dummy variable that equals one if a branch is in the same state with the headquarter of the bank, and zero otherwise.	SOD
New	A dummy variable that equals one if a branch was established within the past five years, and zero otherwise.	SOD
Bank Characteristics		
Loan	The share of loans in total assets.	Call Report
ln(Loan)	The natural logarithm of total loans.	Call Report
ROA	The ratio of the annualized net income to gross total assets.	Call Report
Liquidity	Cash divided by bank total deposits.	Call Report
Sensitivity	The sensitivity to interest rate risk, defined as the ratio of the absolute difference between short-term assets and short-term liabilities to gross total assets.	Call Report
Small	A dummy variable that equals one if a bank has less than two billion dollars in assets, and zero otherwise.	Call Report
Local	A dummy variable that equals one if a bank obtains more than 65% of its deposits from a single county, and zero otherwise.	SOD
County Characteristics		
Branch	Number of bank branches per 1,000 population in the county.	SOD
Deposits per capita	Amount of bank deposits per capita.	SOD
HHI	The Herfindahl-Hirschmann index of deposits at all bank branches in the county.	SOD
Unemployment	Local unemployment rate.	ACS
Population	Local total population size in millions.	ACS
White	Share of white people in local population.	ACS
Female	Share of female in local population.	ACS
Education	The population that are over 25 years and with high school education (or higher) divided by the total population older than 25.	ACS
Income	Income (in thousand dollars) per capita.	ACS
Senior	The share of population that is over 65 years old.	ACS
ManufacturingLabor	The share of labor working in manufacturing industry.	ACS
InformationLabor	The share of labor working in information industry.	ACS

Table A2. Summary Statistics of Natural Disasters

This table presents the summary statistics for the Google Rating-FEMA-HMDA-merged sample. Panel A shows the frequency and severity of the natural disasters used by the sample. Panel B shows the summary statistics of the key variables in the sample.

Panel A: Frequency and Severity of Natural Disasters			
Disaster Type	**Frequency**	**Average Number of Counties Affected**	**Total Number of Counties Affected**
Severe Storm	55	9.58	527
Flood	48	10.19	489
Hurricane	15	17.00	255
Snow	10	15.40	154
Tornado	4	1.25	5
Severe Ice Storm	3	15.00	45
Coastal Storm	1	1.00	1
Mud/Landslide	1	8.00	8
Volcano	1	1.00	1
Total	138	10.76	1,485

Panel B: Google Rating-FEMA-HMDA-merged Sample				
	N	**Mean**	**Median**	**S.D.**
Mortgage Demand				
Application	37,178	82.100	31.000	153.000
ln(Applications)	37,178	3.280	3.470	1.670
Google Rating				
HighACC	37,178	0.248	0.000	0.432
NumReviews	37,178	8.120	3.000	19.3
Bank Characteristics				
ln(Loan)	37,178	14.400	13.700	2.800
ROA	37,178	0.005	0.005	0.002
Liquidity	37,178	0.060	0.041	0.061
Sensitivity	37,178	-0.130	-0.126	0.124
Small	37,173	0.465	0.000	0.499
Local	37,178	0.206	0.000	0.404
Important	37,178	0.244	0.000	0.430
County Characteristics				
Branch	37,178	382	338	182
Deposits per capita	37,178	22.500	18.800	13.000
Unemployment	37,178	0.067	0.064	0.025
Population	37,178	0.273	0.095	0.451
White	37,178	0.823	0.866	0.140
Female	37,178	0.504	0.507	0.014
Education	37,178	0.876	0.889	0.058
Income	37,178	28.100	27.100	6.960
Senior	37,178	0.156	0.151	0.042
ManufacturingLabor	37,178	0.119	0.106	0.063
InformationLabor	37,178	0.017	0.016	0.008

Table A3. Topic Word List

Accessibility			Hospitality			Product			Facility		
Word	**Fweight**	**Frequency**	**Word**	**Fweight**	**Frequency**	**Word**	**Fweight**	**Frequency**	**Word**	**Fweight**	**Frequency**
time	3,113.58	68,943	experience	1,900.42	30,401	fees	633.23	14,270	atm	2,367.55	31,162
place	2,125.39	22,202	see	530.17	14,604	loan	518.99	14,531	inside	598.20	11,617
wait	1,840.16	31,216	walk	355.75	7,971	checking	395.19	11,206	parking	569.96	7,413
waiting	1,023.72	20,039	deal	343.90	7,115	charge	359.31	9,210	clean	508.73	4,249
phone	1,020.38	20,817	helping	329.62	7,012	fee	353.70	10,384	atms	339.60	4,343
take	878.39	21,484	smile	327.72	5,410	mortgage	233.95	6,596	building	297.68	4,166
come	852.07	20,060	attitude	316.62	6,862	savings	204.18	6,217	front	274.11	7,110
times	767.44	17,536	visit	309.83	6,100	charged	164.66	5,242	debit	250.02	8,352
person	710.55	18,391	talk	295.87	7,471	rates	148.81	2,617	window	248.78	5,772
day	694.66	20,878	welcoming	221.17	2,603	interest	140.27	4,055	machine	221.33	5,239
lines	670.36	7,828	speak	218.95	6,512	charges	135.25	3,936	lobby	201.68	4,266
hour	594.33	11,487	reviews	190.96	5,077	rate	130.42	3,460	outside	196.41	3,960
busy	577.94	8,886	greeted	180.04	4,258	loans	123.09	2,860	app	187.20	4,339
took	517.35	14,331	review	171.17	5,835	acct	66.74	2,067	atmosphere	174.44	1,723
called	479.12	17,972	experiences	168.18	3,150	saving	37.28	1,014	desk	129.55	3,583
waited	446.21	9,727	dealt	165.92	3,416	refinance	34.00	1,047	windows	121.02	2,138
area	363.73	7,147	assist	162.99	3,688	score	31.81	1,140	machines	119.63	2,065
usually	309.11	5,551	experienced	150.14	3,096	cd	30.20	768	view	106.04	908
takes	297.79	5,796	fix	139.85	3,394	lower	28.39	837	environment	103.18	1,078
branches	297.62	6,580	welcome	129.16	2,271	terms	27.24	802	broken	99.37	1,451
front	274.11	7,110	greet	125.23	2,454	lending	26.92	640	doors	72.27	1,493
least	269.76	7,000	remember	125.00	2,624	lender	26.13	796	park	71.67	1,583
week	268.12	7,959	assistance	109.63	2,484	added	25.61	919	facility	67.89	973
mins	263.81	5,446	smiling	99.10	1,391	investment	25.03	641	space	60.52	961
store	256.75	3,743	handle	96.52	2,613	financing	24.10	622	views	58.34	355
window	248.78	5,772	explain	88.53	2,992	finance	23.36	657	accessible	56.07	693
hold	242.13	7,505	resolve	81.28	2,216	bucks	23.02	541	cars	52.92	1,284
locations	218.70	4,174	meet	79.12	1,905	product	22.78	562	traffic	50.81	1,002
counter	205.77	5,039	serve	76.36	1,483	mortgages	21.23	542	floor	46.36	887

Table A4. Reputation Shock and Deposit Growth

This table re-estimates Equation 4 using the same sample across all columns. *DepositGrowth* is the annual growth in branch deposits. *Rep_J* is a dummy variable that equals one if the bank has an increase in the RepRisk Index by at least J (J=10, 15, 20, or 25) in the past 12 months, and zero if the increase is below J (instead of 10 as in Table 5). *Deposits* is the amount of branch deposits. *BetterRate* is a dummy variable that equals one if the average rate of 12-month CD products at the branch is higher than the county median, and zero otherwise. *CountyShare* is the market share of the branch in the county by deposits. *Loan* is the share of loans in total assets. *ROA* is the bank's return on assets. *Liquidity* is cash divided by total deposits. *Sensitivity* is the sensitivity to interest rate risk. Standard errors are clustered at the branch level and t-statistics are shown in parentheses. Statistical significance at the 10%, 5% and 1% levels is denoted by *, ** and ***, respectively.

	DepositGrowth				
	(1)	(2)	(3)	(4)	(5)
Rep_10	-0.687***				
	(-3.90)				
Rep_15		-1.064***			
		(-6.10)			
Rep_20			-0.242		
			(-1.07)		
Rep_25				-0.734***	
				(-2.89)	
Rep_Chg					-0.034***
					(-3.72)
Deposits	-0.152***	-0.152***	-0.152***	-0.152***	-0.152***
	(-12.34)	(-12.34)	(-12.33)	(-12.33)	(-12.34)
BetterRate	0.015	0.026	-0.021	-0.087	-0.048
	(0.04)	(0.07)	(-0.06)	(-0.23)	(-0.13)
CountyShare	-225.506***	-225.226***	-225.371***	-225.320***	-225.369***
	(-14.95)	(-14.92)	(-14.93)	(-14.92)	(-14.93)
Loan	3.893***	5.390***	4.026***	4.143***	4.433***
	(3.79)	(5.07)	(3.92)	(4.05)	(4.27)
ROA	34.706	44.061*	29.485	35.466	40.329
	(1.32)	(1.65)	(1.10)	(1.33)	(1.52)
Liquidity	2.543*	3.433**	3.652***	3.786***	3.523**
	(1.78)	(2.44)	(2.58)	(2.69)	(2.51)
Sensitivity	5.637***	5.969***	5.625***	5.682***	5.774***
	(4.41)	(4.67)	(4.40)	(4.45)	(4.52)
Branch FE	+	+	+	+	+
County × Year FE	+	+	+	+	+
Observations	135,834	135,834	135,834	135,834	135,834
Adjusted R^2	0.157	0.157	0.156	0.157	0.157

Table A5. The Effects of Decomposed Topic ACC

The following tables reports the complete tables of Table 9.

Panel A

	DepositGrowth			
	Rep_10=1	Rep_15=1	Rep_20=1	Rep_25=1
	(1)	(2)	(3)	(4)
Accessibility	2.054***	3.388***	3.758**	4.268**
	(3.03)	(3.53)	(2.38)	(2.32)
NumReviews	0.038**	0.038	-0.052	-0.152
	(2.05)	(1.10)	(-0.54)	(-1.38)
Deposits	-0.018***	-0.013***	-0.008***	-0.004
	(-17.39)	(-7.93)	(-2.61)	(-1.06)
BetterRate	6.412***	7.824***	17.183***	16.461***
	(4.10)	(3.09)	(4.40)	(3.84)
CountyShare	-16.157***	-20.018***	-25.236***	-24.482**
	(-4.54)	(-3.94)	(-2.63)	(-2.08)
New	33.121***	30.458***	40.387***	42.052***
	(19.42)	(10.48)	(8.72)	(8.29)
RateSetter	-17.816***	-13.855***	-12.061***	-14.879***
	(-12.85)	(-7.44)	(-4.39)	(-4.46)
Bank × County × Shock FE	+	+	+	+
Observations	62,128	28,380	11,628	8,021
Adjusted R^2	0.153	0.128	0.152	0.168

Panel B

	DepositGrowth			
	Rep_10=1	Rep_15=1	Rep_20=1	Rep_25=1
	(1)	(2)	(3)	(4)
Hospitality	1.622	1.806	5.785	9.480*
	(1.11)	(0.87)	(1.42)	(1.92)
NumReviews	0.031*	0.026	-0.068	-0.172
	(1.66)	(0.76)	(-0.72)	(-1.57)
Deposits	-0.018***	-0.013***	-0.008***	-0.004
	(-17.36)	(-7.92)	(-2.59)	(-1.04)
BetterRate	6.430***	7.843***	17.220***	16.437***
	(4.11)	(3.10)	(4.41)	(3.83)
CountyShare	-16.182***	-20.078***	-25.113***	-24.115**
	(-4.55)	(-3.95)	(-2.63)	(-2.05)
New	33.153***	30.479***	40.421***	42.088***
	(19.43)	(10.47)	(8.73)	(8.31)
RateSetter	-17.825***	-13.854***	-12.018***	-14.828***
	(-12.85)	(-7.43)	(-4.38)	(-4.45)
Bank × County × Shock FE	+	+	+	+
Observations	62,128	28,380	11,628	8,021
Adjusted R^2	0.153	0.127	0.152	0.168

Panel C

	DepositGrowth			
	Rep_10=1	Rep_15=1	Rep_20=1	Rep_25=1
	(1)	(2)	(3)	(4)
Product	1.436	-0.508	-3.237	-4.947
	(0.74)	(-0.18)	(-0.75)	(-0.75)
NumReviews	0.030	0.025	-0.073	-0.182*
	(1.63)	(0.72)	(-0.77)	(-1.65)
Deposits	-0.018***	-0.013***	-0.008***	-0.004
	(-17.35)	(-7.92)	(-2.59)	(-1.04)
BetterRate	6.432***	7.842***	17.211***	16.485***
	(4.11)	(3.10)	(4.40)	(3.83)
CountyShare	-16.215***	-20.159***	-25.471***	-24.966**
	(-4.56)	(-3.96)	(-2.66)	(-2.12)
New	33.157***	30.490***	40.440***	42.093***
	(19.43)	(10.48)	(8.73)	(8.29)
RateSetter	-17.833***	-13.871***	-12.054***	-14.861***
	(-12.86)	(-7.44)	(-4.39)	(-4.46)
Bank × County × Shock FE	+	+	+	+
Observations	62,128	28,380	11,628	8,021
Adjusted R^2	0.153	0.127	0.152	0.167

Panel D

	DepositGrowth			
	Rep_10=1	Rep_15=1	Rep_20=1	Rep_25=1
	(1)	(2)	(3)	(4)
Facility	1.792*	2.683*	2.786	2.109
	(1.74)	(1.70)	(1.20)	(0.74)
NumReviews	0.031*	0.026	-0.070	-0.179
	(1.69)	(0.76)	(-0.74)	(-1.63)
Deposits	-0.018***	-0.013***	-0.008***	-0.004
	(-17.36)	(-7.92)	(-2.59)	(-1.03)
BetterRate	6.422***	7.839***	17.214***	16.503***
	(4.10)	(3.09)	(4.40)	(3.83)
CountyShare	-16.240***	-20.154***	-25.443***	-24.832**
	(-4.56)	(-3.96)	(-2.66)	(-2.11)
New	33.137***	30.450***	40.378***	42.026***
	(19.41)	(10.46)	(8.71)	(8.29)
RateSetter	-17.829***	-13.852***	-12.022***	-14.820***
	(-12.85)	(-7.43)	(-4.38)	(-4.45)
Bank × County × Shock FE	+	+	+	+
Observations	62,128	28,380	11,628	8,021
Adjusted R^2	0.153	0.127	0.152	0.167

Table A6. Reputation Shock, ACC, and Deposit Growth - A Triple-difference-in-differences Approach

This table reports the results of a triple-difference-in-differences approach that estimates the effects of branch-level ACC on mitigating the negative effects of reputation shock on deposit growth. *DepositGrowth* is the annual growth in branch deposits. The treatment group ($Treat$=1) includes branches that experienced a reputation shock over the year (a shock in RepRisk index of at least 10, 15, 20, or 25), but did not experience any shock in the preceding year. For each treatment branch, the control branches ($Treat$=0) include all branches in the same county but did not experience any reputation shocks over the past two years. The treatment branch and its control branches are considered a cohort. *Post* is equal to one for the treatment year, and zero for the control year. *ACC* is the average Google rating of all the existing Google reviews on the branch. Standard errors are clustered at the cohort level and t-statistics are shown in parentheses. Statistical significance at the 10%, 5% and 1% levels is denoted by *, ** and ***, respectively.

Panel A

	DepositGrowth			
	Rep_10=1	Rep_15=1	Rep_20=1	Rep_25=1
	(1)	(2)	(3)	(4)
Treat × Post × ACC	1.663***	1.637***	1.640***	1.591***
	(4.16)	(3.99)	(3.99)	(3.32)
Treat × Post	-6.495***	-6.698***	-6.693***	-7.848***
	(-15.20)	(-15.18)	(-15.14)	(-15.18)
Treat × ACC	-0.100	-0.142	-0.147	-0.032
	(-0.36)	(-0.50)	(-0.51)	(-0.09)
Post × ACC	-1.674***	-1.760***	-1.763***	-1.835***
	(-5.40)	(-5.45)	(-5.45)	(-4.84)
Treat	2.240***	2.417***	2.388***	-0.184
	(3.44)	(3.62)	(3.41)	(-0.10)
Post	5.992***	6.046***	6.044***	7.940***
	(15.92)	(15.44)	(15.41)	(17.59)
ACC	0.426*	0.499**	0.497**	0.462*
	(1.87)	(2.16)	(2.14)	(1.66)
Controls	+	+	+	+
Cohort FE	+	+	+	+
Bank × County FE	+	+	+	+
Observations	40,187	38,577	38,502	28,015
Adjusted R^2	0.174	0.175	0.175	0.161

Panel B

	DepositGrowth			
	Rep_10=1	Rep_15=1	Rep_20=1	Rep_25=1
	(1)	(2)	(3)	(4)
Treat × Post × ACC	1.247***	1.112***	1.126***	1.050**
	(2.93)	(2.58)	(2.61)	(2.18)
Treat × ACC	0.081	0.160	0.146	0.106
	(0.30)	(0.59)	(0.54)	(0.34)
Post × ACC	-0.810**	-0.718**	-0.736**	-0.843**
	(-2.33)	(-2.03)	(-2.08)	(-2.15)
Treat	-4.733*	-4.703*	-4.707*	-12.337***
	(-1.92)	(-1.91)	(-1.91)	(-2.67)
ACC	-0.050	-0.110	-0.102	0.008
	(-0.24)	(-0.52)	(-0.48)	(0.03)
Controls	+	+	+	+
Cohort FE	+	+	+	+
Bank × County × Year FE	+	+	+	+
Observations	38,148	36,583	36,516	26,307
Adjusted R^2	0.402	0.403	0.403	0.427

Table A7. Reputation Shock, ACC, and Deposit Growth: ZIP Code Fixed Effects
This table re-estimates Equation 5 using bank-ZIP Code-shock fixed effects. The observations are at the branch-year level, where branches are the branch offices of banks that experienced a reputation shock in the past 12 months (an increase in RepRisk index of at least 10, 15, 20, or 25 corresponds to columns 1 to 4, respectively) and years are the years of reputation shocks. *DepositGrowth* is the annual growth in branch deposits. *ACC* is the average Google rating of all the existing Google reviews on the branch. *NumReviews* is the number of Google ratings. *Deposits* is the amount of branch deposits. *BetterRate* is a dummy variable that equals one if the average rate of 12-month CD products is higher than the county median, and zero otherwise. *CountyShare* is the market share of the branch in the county by deposits. *New* is a dummy variable that equals one if a branch was established within the past five years, and zero otherwise. *RateSetter* is a dummy variable that equals one if a branch is a local rate setter, and zero otherwise. Standard errors are clustered at the bank-county-shock year level and t-statistics are shown in parentheses. Statistical significance at the 10%, 5% and 1% levels is denoted by *, ** and ***, respectively.

	DepositGrowth			
	Rep_10=1	Rep_15=1	Rep_20=1	Rep_25=1
	(1)	(2)	(3)	(4)
ACC	0.375**	0.631**	0.693*	0.739
	(2.11)	(2.54)	(1.75)	(1.55)
NumReviews	-0.020	-0.083	-0.348	-0.515
	(-0.42)	(-0.91)	(-1.20)	(-1.30)
Deposits	-0.023***	-0.020***	-0.009*	-0.006
	(-13.38)	(-6.68)	(-1.80)	(-0.98)
BetterRate	8.284***	11.076***	27.775***	31.812***
	(3.76)	(3.40)	(5.14)	(5.25)
CountyShare	-17.179***	-25.231***	-39.178**	-48.685*
	(-2.98)	(-3.01)	(-2.27)	(-1.88)
New	33.618***	32.641***	44.990***	47.242***
	(13.32)	(7.97)	(6.98)	(6.48)
RateSetter	-19.443***	-15.205***	-11.208**	-9.251
	(-8.49)	(-4.79)	(-2.04)	(-1.25)
Bank × ZIP Code × Shock FE	+	+	+	+
Observations	22,818	9,384	2,995	2,106
Adjusted R^2	0.141	0.112	0.159	0.192

Table A8. The Effects of Reputation Shock on County-level Deposit Growth
This table reports the results on the OLS panel regressions of yearly county-level deposit growth on the share of branch deposits that is subject to reputation damage. *DepositGrowth* is the county-level deposit growth. *Share_J* is the share of a county's bank deposits that is subject to a jump in the RepRisk Index by more than J (J=10, 15, 20, or 25). *Deposits* is the total deposits of all bank branches in the county. HHI is the is the Herfindahl-Hirschmann index of deposits at all bank branches in the county. Standard errors are clustered at the county level and t-statistics are shown in parentheses. Statistical significance at the 10%, 5% and 1% levels is denoted by *, ** and ***, respectively.

	DepositGrowth			
	(1)	(2)	(3)	(4)
	J=10	J=15	J=20	J=25
Share_J	-1.887	-1.743	-2.132*	-2.855**
	(-1.23)	(-1.42)	(-1.80)	(-1.99)
Deposits_County	-0.097	-0.099	-0.099	-0.099
	(-1.34)	(-1.35)	(-1.35)	(-1.36)
Branch	9.014*	9.117*	9.198*	9.224*
	(1.80)	(1.84)	(1.86)	(1.86)
HHI	29.144**	29.252**	29.473**	29.498**
	(2.33)	(2.35)	(2.37)	(2.37)
County FE	+	+	+	+
Year FE	+	+	+	+
Observations	12,734	12,734	12,734	12,734
Adjusted R^2	0.215	0.215	0.215	0.215

Table A9. ACC and Mortgage Demand During Natural Disasters
The following table reports the complete Table 10.

	ln(Applications)			
	(1)	(2)	(3)	(4)
Treat × Post × HighACC	0.203***	0.199***	0.149**	0.184***
	(3.57)	(3.15)	(2.53)	(3.05)
Treat × Post	0.355***	0.343***	0.246***	0.269***
	(13.43)	(11.95)	(9.79)	(10.82)
Treat × HighACC	-0.196***	-0.176***	-0.243***	-0.200***
	(-5.43)	(-4.17)	(-5.42)	(-4.14)
Post × HighACC	-0.722***	-0.756***	-0.568***	-0.710***
	(-20.96)	(-19.70)	(-17.26)	(-20.42)
Treat	-0.150***	-0.147***	0.038*	-0.131***
	(-9.72)	(-8.90)	(1.66)	(-5.23)
Post	-0.849***	-0.899***	-0.271***	-0.668***
	(-48.98)	(-45.42)	(-18.23)	(-31.04)
HighACC	0.621***	0.649***	0.720***	0.778***
	(26.75)	(23.86)	(23.09)	(23.97)
Lag ln(Applications)	0.757***	0.652***	0.112***	0.092***
	(172.97)	(93.75)	(7.79)	(7.00)
ln(Loan)	0.029***	0.084***	0.068***	0.050***
	(17.27)	(18.13)	(15.33)	(13.09)
ROA	-6.647***	-91.712***	-67.331***	-50.719***
	(-4.29)	(-15.03)	(-13.74)	(-12.01)
Liquidity	-0.589***	-0.275	0.032	-0.045
	(-8.47)	(-0.93)	(0.13)	(-0.21)
Sensitivity	0.400***	2.542***	1.691***	2.270***
	(11.51)	(18.53)	(14.09)	(21.27)
Missing	0.067***	0.110***	0.235***	0.095***
	(6.12)	(7.85)	(7.39)	(3.41)
Small	0.077***	0.245	0.072	-0.011
	(8.28)	(1.63)	(0.67)	(-0.12)
Local	-0.024**	-0.252***	-0.278***	-0.226***
	(-2.43)	(-3.32)	(-4.75)	(-4.28)
Important	0.114***	0.237***	0.072	0.059
	(11.78)	(19.59)	(1.14)	(1.08)
Branch	-0.000***	-0.000***	0.002***	0.000
	(-8.22)	(-12.46)	(4.15)	(0.73)
Deposits per capita	0.002***	0.001***	0.015**	0.023***
	(4.44)	(3.20)	(2.19)	(3.66)
Unemployment	-1.995***	-2.739***	-5.609***	-13.045***
	(-8.23)	(-10.59)	(-3.90)	(-11.79)
Population	0.069***	0.214***	22.946***	17.777***
	(5.56)	(15.85)	(14.84)	(12.36)
White	0.154***	0.117***	9.481***	6.267***
	(3.86)	(2.71)	(4.78)	(4.77)
Female	0.897***	1.624***	-2.991	-6.690**
	(3.41)	(5.75)	(-0.67)	(-2.01)
Education	0.829***	1.268***	6.882***	10.437***
	(8.40)	(11.41)	(4.63)	(8.46)
Income	-0.013***	-0.015***	-0.677***	-0.438***
	(-14.07)	(-14.45)	(-41.82)	(-28.26)
Senior	-0.241**	-0.395***	-33.008***	1.204
	(-2.13)	(-3.53)	(-9.65)	(0.43)
ManufacturingLabor	0.041	0.096	3.592***	3.343***
	(0.59)	(1.23)	(2.69)	(3.12)
InformationLabor	4.049***	3.585***	-1.523	3.551
	(6.35)	(5.24)	(-0.38)	(1.13)
Disaster Year × State FEs	+			+
Disaster Year × State × Bank FEs		+		
Bank × County FEs			+	+
Observations	37,173	37,170	37,170	37,170
Adjusted R^2	0.691	0.690	0.606	0.655

Table A10. The Differential Effects of Topic Ratings During Natural Disasters

This table reports the results on triple difference regressions that exam the differential effects of topic ratings on mortgage demand following natural disasters. *High Topic Rating* is a dummy variable that equals one if the topic rating of a bank in a county is at the top tercile in the state in the year, and zero if it is at the bottom tercile. The topic rating (*Accessibility*, *Product*, *Hospitality*, *Facility*) is the simple average topic rating of all the reviews of the bank in the county up to the current year, where topic rating is defined as the relative word mentioning on a topic (frequency of key words associated with a specific topic scaled by the total number of words in the review) times the rating of the review. The key words for topics are listed in Appendix A3. *Treat* is a dummy variable that equals one for the disaster affected counties, and zero for control counties. *Post* is a dummy variable that equals one for the disaster incidence year, and zero for the preceding year. Control variables include *Lag ln(Applications)*, *ln(Loan)*, *ROA*, *Liquidity*, *Sensitivity*, *Missing*, *Small*, *Local*, *Important*, *Branch*, *Deposit per Capita*, *Unemployment*, *Population*, *White*, *Female*, *Education*, *Income*, *Senior*, *Manufacturing Labor*, *Information Labor*. Standard errors are clustered at the county-bank level and t-statistics are shown in parentheses. Statistical significance at the 10%, 5% and 1% levels is denoted by *, ** and ***, respectively.

	ln(Applications)							
	Accessibility		Product		Hospitality		Facility	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treat × Post × HighTopicACC	0.206**	0.188**	0.193*	0.193*	0.296***	0.339***	0.319***	0.383***
	(2.55)	(2.37)	(1.74)	(1.79)	(3.46)	(4.08)	(3.17)	(3.86)
Treat × Post	0.425***	0.358***	0.434***	0.363***	0.396***	0.323***	0.411***	0.333***
	(16.53)	(16.11)	(17.10)	(16.66)	(15.61)	(14.84)	(16.21)	(15.29)
Treat × HighTopicACC	-0.091*	-0.172***	-0.109	-0.262***	-0.102**	-0.282***	-0.115*	-0.259***
	(-1.80)	(-2.63)	(-1.59)	(-2.99)	(-2.00)	(-4.21)	(-1.89)	(-3.07)
Post × HighTopicACC	-1.103***	-1.074***	-1.314***	-1.279***	-1.274***	-1.253***	-1.378***	-1.412***
	(-23.94)	(-24.86)	(-21.23)	(-22.15)	(-26.34)	(-28.00)	(-24.42)	(-26.81)
Treat	-0.209***	-0.194***	-0.207***	-0.192***	-0.197***	-0.179***	-0.203***	-0.193***
	(-13.67)	(-8.27)	(-13.93)	(-8.37)	(-12.94)	(-7.68)	(-13.49)	(-8.36)
Post	-1.130***	-0.852***	-1.201***	-0.904***	-1.140***	-0.852***	-1.188***	-0.884***
	(-65.56)	(-41.31)	(-71.63)	(-44.06)	(-68.63)	(-41.61)	(-71.46)	(-42.97)
HighTopicACC	0.680***	0.769***	0.763***	0.823***	0.711***	0.709***	0.816***	0.952***
	(22.58)	(17.72)	(19.46)	(14.19)	(23.28)	(15.39)	(22.27)	(17.61)
Controls	+	+	+	+	+	+	+	+
Disaster Year × State × Bank FE	+		+		+		+	
Disaster Year × State FE		+		+		+		+
Bank × County FE		+		+		+		+
Observations	42,476	42,478	42,826	42,828	42,922	42,924	42,948	42,950
$Adjusted R^2$	0.684	0.64	0.682	0.638	0.685	0.642	0.683	0.64

Table A11. ACC and Mortgage Demand by Loan Purpose

This table re-estimates Table 10 by examining mortgage applications by loan purpose (new purpose or refinance). *Treat* is a dummy variable that equals one for the disaster affected counties, and zero for control counties. *Post* is a dummy variable that equals one for the disaster incidence year, and zero for the preceding year. *HighACC* is a bank-county-year-level dummy variable that equals one if the bank's average Google rating in the county is at the top tercile among all banks within the same state, and zero if it is at the bottom tercile. *ln*(*Applications*) is the natural logarithm of the annual number of mortgage applications to the bank in the a county. Control variables include *Lag ln*(*Applications*), *ln*(*Loan*), *ROA*, *Liquidity*, *Sensitivity*, *Missing*, *Small*, *Local*, *Important*, *Branch*, *Deposit per Capita*, *Unemployment*, *Population*, *White*, *Female*, *Education*, *Income*, *Senior*, *Manufacturing Labor*, *Information Labor*. Standard errors are clustered at the county-bank level and t-statistics are shown in parentheses. Statistical significance at the 10%, 5% and 1% levels is denoted by *, ** and ***, respectively.

	Log Applications							
	New Purchase				Refinance			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treat × Post × HighACC	0.182***	0.166***	0.112**	0.138**	0.132***	0.134**	0.096*	0.129**
	(3.47)	(2.82)	(2.10)	(2.55)	(2.60)	(2.38)	(1.83)	(2.42)
Treat × Post	0.285***	0.283***	0.193***	0.212***	0.309***	0.293***	0.214***	0.235***
	(11.46)	(10.48)	(8.36)	(9.26)	(12.26)	(10.78)	(9.15)	(10.11)
Treat × HighACC	-0.177***	-0.163***	-0.197***	-0.157***	-0.154***	-0.124***	-0.197***	-0.162***
	(-5.36)	(-4.12)	(-4.86)	(-3.61)	(-4.70)	(-3.29)	(-4.87)	(-3.78)
Post × HighACC	-0.561***	-0.599***	-0.460***	-0.569***	-0.577***	-0.592***	-0.426***	-0.546***
	(-18.13)	(-17.30)	(-15.71)	(-18.48)	(-18.78)	(-17.33)	(-14.60)	(-17.78)
Treat	-0.133***	-0.132***	0.019	-0.111***	-0.122***	-0.118***	0.035	-0.108***
	(-9.02)	(-8.20)	(0.90)	(-4.70)	(-8.32)	(-7.42)	(1.62)	(-4.61)
Post	-0.817***	-0.852***	-0.244***	-0.568***	-0.742***	-0.789***	-0.241***	-0.581***
	(-52.19)	(-47.45)	(-18.18)	(-27.83)	(-45.16)	(-42.36)	(-17.52)	(-28.68)
HighACC	0.493***	0.531***	0.572***	0.615***	0.526***	0.541***	0.613***	0.659***
	(23.54)	(21.38)	(20.42)	(21.02)	(25.09)	(22.21)	(21.83)	(22.85)
Controls	+	+	+	+	+	+	+	+
Disaster Year × State FEs	+			+	+			+
Disaster Year × State × Bank FEs		+				+		
Bank × County FEs			+	+			+	+
Observations	33,613	33,610	33,610	33,610	35433.000	35,430	35,430	35,430
Adjusted R^2	0.663	0.667	0.614	0.655	0.703	0.706	0.644	0.685