Trademarks in Banking*

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Abstract

One in five banks in the United States share a similar name. This can increase the likelihood of confusion among customers in the event of an idiosyncratic shock to a similarly named bank. We find that banks that share their name with a failed bank experience a half percent drop in transaction deposits relative to banks with similar characteristics but different name. This effect doubles for failures that are covered in media. We rationalize our findings via a model of financial contagion without fundamental linkages. Our model explains that when distinguishing banks is more costly due to similar trademarks, depositors are more likely to confuse their banks' condition resulting in financial contagion.

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JEL Classifications: G21; G14; G30

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1 Introduction

A trademark is a sign - logo, sound or color - used by a firm to identify a product or service. Unlike a patent, which is a property interest held by the proprietor, trademarks create distinctiveness. They convey information about the quality of a product or service, even when quality is not observable. As such, they help resolve an information asymmetry problem (e.g., Akerlof, 1970). Due to their ability to convey information, the law protects the owners of trademarks from the use of similar marks. Consumers may also benefit because owners may be incentivized to deliver a higher level of quality consistent with theories of trademarks as tradeable assets (e.g., Shapiro, 1982, Landes and Posner, 1987, Aghion and Howitt, 1992, Tirole, 1996).

A firm's name is the most important trademark (e.g., Tadelis, 1999). Despite extensive legal protections, it is not uncommon for firms to use similarly sounding names. The use of similarly sounding names, however, can increase the likelihood of confusion among customers if a similarly named firm experiences stress. This issue is probably more acute in the banking industry, where spillovers to the system as a whole are more likely due to banks' role as liquidity providers (e.g., Kashyap, Rajan, and Stein, 2002).

Several cases of runs on banks that have similarly sounding names with banks experiencing stress provide a useful illustration. For example, following the rescue announcement of the San Francisco-based First Republic Bank on March 17, 2023, the stock of Pennsylvania-based Republic First Bankcorp plunged by nearly 30%. This marked Republic First's worst single-day performance since 1994 despite assurances by the president and CEO of the bank that *"amid everything going on, Republic Bank would like to make very clear: we are Republic Bank, Inc. (FRBK-Red/Blue Logo); we are NOT First Republic Bank (FRC-Green Logo)"*.[1] Other banks – Signature Bank of Arkansas and Signature Bank Chicago – released similar statements after Signature Bank New York showed the first signs of stress in March 2023. [2] On July 25, 2008, following the closure of the First National Bank of Reno, Nevada, and the First Heritage Bank of Newport Beach, California, by the Office of the Comptroller of the Currency (OCC), the president and CEO of Heritage Bank of Reno, Nevada, spent days assuring customers who saw the name Heritage in the news that his bank was financially sound.[3]

[1] Banking Dive, "Republic First Bank CEO to customers, investors: We are not First Republic".

[2] See Appendix A.

[3] Reno Gazette, "Bank reopens with new name", 29, July 2008.

These episodes are by no means a U.S. or recent phenomenon. On September 4, 2014, in India, following the news coverage by a Bengali newspaper that the Jalpaiguri Cooperative Bank Limited did not have the required RBI licence to be an active bank, depositors became confused with the name and turned up at the Jalpaiguri Central Cooperative Bank branches wanting to withdraw their money.[4] In October 1934, depositors ran on the Amoy branch of the National Industrial Bank of China. The reason was a rumour that the bank's head office in Shanghai was closed and the bank had gone out of business. The truth, however, was that a similarly sounding bank in Shanghai had closed on the exact same day.[5] In September 1985, as concerns mounted over the health of small Canadian banks, a run developed at the Continental Bank of Canada. According to its president, *"the bank was also hurt by statements in the media confusing it and a troubled trust company with a similar name"*, eventually resulting in a support package from a group of financial institutions and the Bank of Canada.[6]

These examples have one thing in common: the use of similarly sounding names can increase the likelihood of confusion among customers in the event of an idiosyncratic shock to a similarly named bank. Confusion may then lead to runs even on well-managed banks that are not in any way related to the stressed bank.

Our paper takes a deep dive into this issue. We study the U.S. banking system due to its structure and historical evolution. When American banking was a local business, the First National Bank of a small town was distinctive enough and unlikely to be confused by another First National Bank two towns over. In fact, the National Bank Act of 1864—a landmark piece of legislation that established the National Banking System in the United States—required banks to include the word "national" in their names and encouraged them to bear numbers (Conley and Hunter, 2007). These naming conventions have persisted into the 21st century. The deregulation of the banking industry and the advent of branch banking in the 1990s have led banks with similarly sounding names chosen in the past to start competing in the same areas, potentially increasing the likelihood of confusion among customers. Confusion may further exacerbate in the era of the Internet and rapid communications.

[4]The Telegraph Online, "Bank licence scare after RBI notice - Depositors panic as officials seek correction on bank name in newspaper".

[5]South China Morning Post, "Run on Amoy Bank. The National Industrial Bank of China. Victim of Rumours", 7, November, 1934.

[6]The Globe and Mail, "Bank receives $2.9 billion in aid Crisis shows few signs of abating", 1, November, 1985.

The first part of the paper establishes facts about bank names and how they evolved over time. We show that the most prevalent words in bank names are "bank" and charter distinctions such as "state" and "national". The type of bank is also a common feature with words like "community", "savings", and "trust" being widely used. As of December 2022, nearly 14% of bank names begin with the word "first", while 11% of bank names begin with one of seven words: "citizens", "peoples", "farmers", "united", "heritage", "liberty", or "american". Nearly 210 (103) banks begin with "First National (State) Bank". These two phrases account for almost 7% of all bank names in 2022. Overall, nearly 20% of bank names begin with a phrase or string that could refer to several banks in 2022. Interestingly, this share has been remarkably stable over the past three decades despite the massive consolidation in the U.S. banking industry.

The prevalence of name commonalities may lead to customers' confusion in the face of a negative event to a similarly sounding bank. We explore this issue next. For identification, we focus on bank failures and compare deposits of banks that share their name with the failed bank (treatment group) to other banks with similar balance sheet characteristics but different name (control group). For example, we compare deposits of Horizon Bank, Nebraska (treatment bank) to Bank of Vernon, Alabama (control bank) before and after the failure of Horizon Bank, Florida (failed bank). Our propensity score matching algorithm ensures that Horizon Bank, Nebraska, and Bank of Vernon, Alabama, have similar balance sheet characteristics, including size, deposits over total assets, loans over total assets and profitability. We also ensure that that Horizon Bank, Nebraska, and Horizon Bank, Florida, have nothing in common but a name.[7] We then treat the failure of Horizon Bank, Florida, as an exogenous event that may (or may not) impact deposits of Horizon Bank, Nebraska. The purpose of the control bank is to inform us what would have happened to the deposits of the Nebraska bank in the absence of the failure of the Florida bank.

Via difference-in-differences regressions, we find strong effects on transaction deposits.[8]. Transaction deposits as a share of total assets fall nearly 0.7% immediately after the associated bank failure and slowly rise over the following two years. This effect is robust to saturated models complete with bank and time fixed effects, as well as the inclusion of banking demand controls proxied by corporate investment in the spirit of Gulen and Ion (2016). This effect is further amplified by the publicity each bank failure receives (akin to a "media multiplier" (e.g., Besley, Fetzer, and

[7]Most banks in our sample are unit banks, so none are part of the same banking group when we study them.

[8]In contrast to time or savings deposits, transactions deposits can be withdrawn *on demand* and is a product consistent with the role of banks as liquidity providers (Kashyap et al., 2002)

Mueller, in press)). We find that when a bank failure is mentioned in the news, transaction deposits over total assets are, on average, nearly 0.8% lower after the associated bank failure and can drop by as much as 1% immediately after the associated bank failure. These results are not driven by specific banks or time periods and indicate that banks that share a similar name with a failed bank experience a significant decline in transaction deposits.

To better assess the economic impact, quantile estimates across all treatment banks in our sample reveal striking insights into the plausible range of effects. We find a one-in-ten chance that the reduction in transaction deposits amounts to 2.14%, or $2.68 million, and a one-in-four chance of a reduction of 1.17%, or $1.47 million. Given that our sample comprises of relatively small community banks, roughly $100 million in total assets, these findings underscore a sizeable economic impact of name-related contagion risk.

We proceed by exploring the effects on lending. We focus on various types of loans using the difference-in-differences setting, and find generally no effect. While consumer loans slightly reduce (by roughly 0.12%), these results suggest that the effect appears predominantly via banks' liabilities and do not significantly hamper credit provisioning.

We rationalize these findings in a model of financial contagion without fundamental linkages. Our benchmark model is based on Diamond and Dybvig (1983) augmented to have a random investment return and considers the environment where there are two ex-ante identical Diamond-Dybvig banks. The banks have no balance sheet linkages, and their asset returns are independent. The realization of their investment returns reveals before depositors make a withdrawal decision, and each of them receives a private signal about the realization. However, the signal is noisy, in the sense that it may or may not represent their corresponding bank. The focal point of our model is the probability that the drawn signal corresponds to their bank, and we study how the posterior belief, influenced by this signal, shapes the incentive of bank runs. In equilibrium, we find that bank run risk decreases when depositors are more certain about whether their received signal corresponds to their bank. When the signal is more precise, those who receive a good signal believe that their bank is more likely to have a good asset, reducing the incentive to run on the bank. When they do not run on the bank, those receiving a bad signal also have less incentive, as the first-mover advantage diminishes. However, when the signal is less precise, even those who receive a good signal still have stronger incentives to run on the bank. Thus, in the sense that a noisier signal makes a bank run more likely to occur, we have *contagion* through depositors' beliefs.

This contagion channel exists if and only if the signal is imperfect.

We extend this model to evaluate how a bank's trademark affects the bank run risk. In particular, we add an ex-ante choice of attention allocation, which determines the precision of the signal. Paying more attention requires resource costs, and the cost parameter represents the similarity of the banks' trademarks. In particular, if the banks share similar trademarks, paying more attention requires more resources. We interpret the effect of this parameter on the equilibrium bank run risk as *trademark risk*. When it is costly for depositors to distinguish banks, depositors rationally choose to pay less attention, making it easier for the private signal to be misidentified, resulting in higher incentives to run on the bank. In other words, similarity of trademarks amplify financial fragility. Lastly, we explore the role of a public signal, which we interpret as media coverage. This public signal appears if and only if at least one bank has a bad investment return, and in this extension, we show how the media can amplify the trademark risk. Our model provides insights into how financial contagion can manifest itself to increased bank run risk when depositors have the possibility of misidentifying the bank.

Related literature: Our paper contributes to several strands of the literature. First, it contributes to the literature on trademarks, which are intangible assets that include logos, sounds or colors (e.g. Milgrom and Roberts, 1992). A large theoretical literature discusses how trademarks can inform consumers about the quality of a service or product (e.g. Akerlof, 1970; Economides, 1988) and incentivize firms to deliver a higher level of quality consistent with theories of trademarks as tradeable assets (e.g. Shapiro, 1982; Landes and Posner, 1987; Tirole, 1996; Marvel and Ye, 2008). The empirical literature on trademarks is considerably smaller and focuses on the relationship between trademarking activity and a firm's market value. For example, in a sample of manufacturing firms between 1995 and 2005, Krasnikov, Mishra, and Orozco (2009) find that a firm's trademark is positively correlated with its cash flow, Tobin's Q, return on assets and stock returns. Similar results are obtained by González-Pedraz and Mayordomo (2012) who study U.S. banks during the same period. Our contribution to this literature is twofold. First, we document facts on the prevalence and evolution of names in the U.S. banking industry over the past three decades. In contrast to sounds, colors or logos, a firm's name is one of its most important trademarks (Tadelis, 1999). Second, we explore how similarities in trademarks can lead to distortions in financial markets. While the literature measuring firm trademarks is nascent, a firm's trademark provides substantial economic value and can make goods and services more recognizable (Desai, Gavrilova, Silva, and Soares, 2022). We contribute by showing how a bank sharing a name with a failed bank can cause depositors to run on an otherwise healthy bank.

Our paper also relates investors' attention allocation and financial contagion. Attention is a scarce cognitive resource (Kahneman, 1973), which investors must choose how to allocate. As economic agents are resource-constrained by time and processing market news, their attention can affect stock prices (e.g., DellaVigna and Pollet, 2009, Da, Engelberg, and Pengjie, 2011). Investors can also misinterpret information, potentially leading to the misvaluation of assets (Hirshleifer, 2001). Even when no new information is provided, stock tickers with similar names have been shown to comove and can bring prices further away from their fundamentals (Rashes, 2001; Balashov and Nikiforov, 2019). Mondria and Quintana-Domeque (2013) explains contagion between markets through investors' re-balancing attention between them when a market experiences a disruption. Our paper considers contagion through investors' limited attention in the context of bank runs. However, neither attention choices nor trademarks have been considered as a contagion channel of bank fragility. The closest contagion channel that has been considered in the context of bank runs is correlation of asset exposures.[9] When banks have common asset exposures, information can cause a bank run. An early model of an information-based bank run is Jacklin and Bhattacharya (1988), and then Chen (1999) shows that bank runs can be triggered by information about another bank when banks have a common exposure. When investors do not know their bank's asset quality, they may use signals about the health of another bank to assess the default probability of their bank, which in turn, may cause a bank run. This common exposure channel has been further explored by Acharya and Yorulmazer (2008b), Acharya and Yorulmazer (2008a), Manz (2010), and Allen, Babus, and Carletti (2012). More recent papers, Trevino (2020) and Ahnert and Bertsch (2022), also consider the environment where banks' fundamentals, and hence asset returns, are correlated. This paper is the first to examine contagion in the absence of fundamental linkages between banks. We instead consider how investors' beliefs, shaped by the noise of signals, drive contagion. The intensity of this noise is determined by the allocation of attention, which is influenced by trademarks.

Finally, we contribute to the literature studying the effect of media on financial markets (e.g. Engelberg and Parsons, 2011, Tetlock, 2007, Dougal, Engelberg, Garcia, and Parsons, 2012, Garmaise, Levi, and Lustig, in press). Our results that the media can exacerbate risks related to

[9]Other channels that are considered in the literature include direct linkages of balance sheets (Allen and Gale, 2000,Kiyotaki and Moore, 2002, Dasgupta, 2004) and common investor base (Goldstein and Pauzner, 2004).

trademarks aligns with recent work by Cookson, Fox, Gil-Bazo, Imbet, and Schiller (2023), who find that activity on X (formerly known as Twitter) amplified balance sheet risk during the 2023 Silicon Valley Bank run, and Croce, Farroni, and Wolfskeil (2020), who illustrate how social media and newspapers accentuate contagion risk emanating from the recent COVID pandemic. With the rise of social media, the effect of trademarks and misinformed depositors could intensify as investors interpret repeated information through such "echo chambers" as genuine information (Jiao, Veiga, and Walther, 2020). Our theoretical framework adds a novel perspective to how media coverage increases fragility depending on the information set of economic agents, similar in spirit to models linking endogenous public information to volatility and crisis episodes (Angeletos and Werning, 2006).

The remainder of the paper is structured as follows. Section II discusses our data. Section III presents facts on bank names, and section IV presents our main results. Section V presents the model, and section VI concludes.

2 Data and Methodology

The two primary data sources are Call Reports for commercial banks in the United States and the FDIC Failed Bank dataset. Both datasets are publicly available. Call Reports contain complete bank names, as well as balance sheet and income statements data on commercial banks. We also use these data to identify banks with similar names to those in the FDIC Failed Bank dataset. The FDIC Failed Bank dataset contains information on 564 banks that failed between 2000 and 2023. Since the bank names in the Call Reports data contain abbreviations, the abbreviations are elongated to match the full name of the FDIC dataset.[10]

Using a fuzzy matching algorithm, we search for matches between the FDIC Failed Bank dataset and the Call Reports data one quarter after the failure of each failed bank. This process results in

[10] After inspecting the individual names, we make the following substitutions to the Call Reports names: County for CTY; Cooperative for CO-OP; Community for CMNTY; Federal Savings & Loan Association for FS&LA; Savings & Loan Association for S&LA; Building & Loan Association for B&LA; Bank for BK; State Savings Bank for SSB; Bank & Trust Company for B&TC; Federal Savings Bank for FSB; Banking for BKG; Savings for SVG and SVGS; Commerce for CMRC; Trust for TR; Savings Bank for SB; State for ST; Financial for FNCL; National Association for NA; National for NAT; National Bank for NB and NBANK; Merchants for MRCH; Company for CO; Trust and Company for TC.

107 failed banks sharing the name of a surviving bank. These 107 failed banks are associated with 1,026 banks that share their name with a failed bank (treatment banks). We drop any treatment bank that does not contain data two years before and after the date of the similarly named failed bank. This restriction reduces the number of treatment banks to 945.

Next, we create a matched sample for a control group using a propensity score matching algorithm. The control group consists of banks that do not share a name with treatment banks, but are similar in notable characteristics, which we restrict to size, deposits over total assets, loans over total assets and profitability (proxied by ROA). We perform the matching using data two years prior to the associated bank failure. We ensure that the failed bank is associated with at least two similarly named banks to ensure an accurate propensity score matching estimate. This restriction reduces the number of treatment banks to 899 banks. After the matching process, we find 894 control banks that meet the matching criteria. It is important to note that some control banks are matched to multiple treatment banks, resulting in a difference in numbers between the 894 control banks and the 899 treatment banks.

Summary statistics for the matched sample can be found in Table 1. These statistics reflect the two years prior to the associated bank failure to ensure that the treatment and control groups are similar along observables. Overall, the total assets for both banks are around $108 million in both groups. Given the size of these banks, the majority of their funding comes from deposits (83% of total deposits in total assets). Given the small size of the banks, these are primarily retail deposits. The table also shows that time deposits over total assets are nearly 39% in both groups. Transaction deposits are slightly higher in the treatment group by 3%, while uninsured deposits represent a small portion of assets, averaging around 1%. Banks in both groups have around 23% of deposits below the $250,000 account limit, and 16% over the same limit. On the asset side, lending in both groups is approximately 60% of their total assets, with the majority of loans being mortgages (40%) followed by C&I (9%) and consumer loans (5%).

3 Facts on U.S. Banks' Names

The National Bank Act of 1864 was a landmark piece of legislation that established the National Banking System in the United States. This legislation imposed a number of requirements on national banks, including the requirement that they include the word "national" in their name.[11] It also encouraged banks to bear numbers in their names. As a result, bank names have been descriptive rather than distinctive over the history of American banking with a large number of banks today having similar sounding names.

Figure 1 shows a word cloud of the most common words in bank names as of December 2022. The most prevalent words are "bank" and charter distinctions such as "state" and "national". The type of bank is also a distinguishing and common feature in bank names, with words like "community", "savings", and "trust" with high usage.

Table 2 shows the percentage of banks with common words and phrases in their names. Because names are often referred to using their first word or words (e.g. "Citibank National Association" is often just referred to as "Citibank" or "Citi"), we show frequencies of names that begin with the specific token, and also names that contain the token anywhere in their bank name. Nearly 14% of bank names begin with the word "first", while 11% of banks begin with one of seven words: "citizens", "peoples", "farmers", "united", "heritage", "liberty", or "american". Table 2 also shows that a select number of phrases used in bank names can refer to a sizable number of banks. "First National Bank" and "First State Bank" appear in the beginning of 210 and 103 bank names, respectively. These two phrases account for nearly 6.6% of bank names in 2022. Overall, 18% of banks begin with a phrase or string that could refer to several banks.

Next, we explore how this commonality evolves over time. The left panel of Figure 2 shows that the prevalence of bank names beginning with these common strings has decreased significantly since the 1990s. In particular, the number of bank names declined by 71%, from 3,500 banks in 1990 to 1,000 banks at the end of 2022. Yet, it remained fairly stable at roughly 20% as a share of all active banks in a given year after we account for the long-term decline in the number of banks in the United States (right panel). In other words, despite the massive consolidation of the banking industry over the past three decades, one in five banks have had a similarly sounding name.

[11] This requirement was intended to distinguish national banks from state-chartered banks.

4 Risks associated with similar trademarks

4.1 Effects on Deposits

We begin our analysis by studying the effects on deposits of banks that have a similarly sounding name with a failed bank. We hypothesize that similarities in bank names may lead to confusion among depositors of a bank in light of the closure of a similarly named bank.

Before turning to our regression specification, we ensure that the sample of banks analyzed exhibits parallel trends before the failure of the associated banks. This is done by comparing the evolution of several relevant variables, including deposits, time deposits, insured deposits, and transaction deposits, all over total assets, as seen in Figure 3. The control group is represented as a solid line and the treatment group as a dashed line, with the values representing the relative growth compared to one year before the associated bank failure. The figure suggests that there are no significant differences across deposits, time deposits, and uninsured deposits before the failure. However, transaction deposits exhibit a significant reduction starting around one quarter before the failure, likely reflecting negative news associated with the upcoming failure. After the associated bank failure, transaction deposits in treatment banks grow at around 2% less compared to one year before and relative to banks belonging to the control group. These results, along with the comparison of other observables two years before the failure presented in Table 1, help establish that the sample of treatment and control banks do not differ significantly along important dimensions ex-ante.

Next, we test whether the difference in transaction deposits holds while including several relevant controls in the following regression specification:

$$\frac{TransactionDeposits}{Assets}_{b,t} = \beta * SimilarName_b * AfterFailure_t + \gamma * SimilarName_b + \alpha * AfterFailure_t + \delta_b + \delta_t + \epsilon_{b,t} \quad (1)$$

where $\frac{TransactionDeposits}{Assets}_{b,t}$ is the amount over total assets of transaction deposits reported by bank b at quarter t, $SimilarName_b$ equals the value of one for banks that share the name of the associated failed bank and zero if not, $AfterFailure_t$ equals the value of one including and after the quarter of the associated bank failure, and zero otherwise. The baseline is the period before the associated bank failure (i.e., each estimated coefficient measures the differential effect after the associated bank failure to the period before the associated bank failure). We include bank fixed effects to control for time-invariant observable and unobservable bank variables, and quarter fixed effects to control for time-varying factors affecting all banks in quarter q.

Our results are presented in Table 3. Column 1, including only bank fixed effects, suggests that transaction deposits over total assets are nearly 0.5% lower after the associated bank failure. Column 2 controls for the quarter, while column 3, our preferred specification, includes lagged controls of the logarithm of total assets, total deposits to total assets, total loans to total assets and profitability (proxied by ROA). In both cases, we see the coefficient remains stable around -0.4%. The coefficients of the $AfterFailure_t$ and $SimilarName_b$ variables are not statistically significant in our preferred specification. This suggests that banks with different (similar) name from the failed bank did not experience a change in their transaction deposits after (before) the associated bank failure (coefficients α and γ,respectively). These results indicate that, relative to banks with different names, banks that share a similar name with a failed bank experience a significant decline in transaction deposits after the associated bank failure. Additionally, Figure 4 shows the coefficient interaction term for each event time, which indicates that transaction deposits over total assets fall nearly 0.7% after the associated bank failure and slowly rise over the following two years.

To better assess the economic impact of our treatment effect, we conducted quantile estimates across all treatment banks in our sample, revealing striking insights into the plausible range of effects. We find a one-in-ten chance that the reduction in transaction deposits amounts to 2.14%, equivalent to a decline of approximately $2.68 million (assuming the average sized bank), and a one-in-four chance of a reduction of 1.17%, equivalent to roughly $1.47 million. These findings underscore the substantial economic consequences of name-related contagion risk on affected banks.

Importantly, our sample comprises of relatively small community banks, roughly $100 million in total assets. Our treatment effect could intensify if much larger banks (e.g. systemically important banks) shared names with failed financial institutions, as their deposit networks are much larger and the asset-side activities span a broader set of operations that could be hampered if a deposit run occurred due to trademark risk. Additionally, Martin, Puri, and Ufier (2018) find that both deposit inflows and outflows occur during times of distress, potentially attenuating the effects we find as we can only infer the difference in the stock of deposits.

In Table 4, we present several robustness tests to ensure that the results are not driven by specific banks or time periods. Column 1 restricts the sample to control banks that are never considered a treated bank (that's why the fixed effect absorbs the coefficient of the $SimilarName_b$ variable), and column 2 restricts the sample to bank failures that occurred between January 1, 2007 to December 31, 2010. Columns 3 and 4 omit the treatment and control banks associated with the two failures of First National Bank and the three failures of First State Banks. These two bank names, which as shown in Table 2 share their name with nearly 200 and 100 banks even in 2022, comprise a large part of the sample. We eliminate them in these robustness tests to alleviate concerns that our results are driven by these bank failures. Column 5 restricts the sample to the time period of one quarter around the time of failure. The results of all these tests suggest that the findings are robust and not driven by specific cases or time periods. In column 6, we control for the average Tobin's Q and cash flows of all firms that exist in the headquarter of a bank to control for the demand for transaction deposits.[12] These variables vary at the bank-quarter level. In the absence of loan-level data, these variables aim to control for corporate investment, which has been shown to be an important determinant of demand for banking services (Gulen and Ion, 2016; Berger, Guedhami, Kim, and Li, 2022)[13]. Our results are little changed when these demand controls are included. Lastly, in column 7, the dependent variable is replaced with logged transaction deposits, and indicates that transaction deposits nominally decline 2% relative to the control banks after the similarly named bank failure.

4.2 Effect of Media Coverage

In this section, we put forth and empirically examine one mechanism behind our results – the influence of media. We hypothesize that when a bank failure is referenced to in the news, the effect would be relatively more pronounced due to the publicity. Column 1 (2) of Table 5 includes observations where the associated bank failure was (not) referenced to in a Reuters headline during the month of the failure. The results indicate that transaction deposits over total assets are nearly 0.8% lower after the associated bank failure was mentioned in Reuters and 0.3% if it was not.

Figure 5 explores how this effect varies over time. Coefficients are displayed relative to event time equal to -2. For those failures that were mentioned in Reuters, transaction deposits in treatment

[12] The Tobin's Q is defined as the market value of assets divided by the book value of assets and cash flows are the sum of earnings before extraordinary items and depreciation.

[13] Our sample consists of mostly small banks, which provide liquidity locally. As such, the headquarter of a bank is also where the bank raises the vast majority of its deposits.

banks dropped by as much as 1% two quarters after the failure. This effect gradually becomes smaller and finally disappears five quarters after the failure (panel A). The effect is short-lived and smaller in magnitude for failures that were not mentioned in Reuters (panel B).

4.3 Effects on Lending

In Table 6, we explore the effects on lending. Columns 1, 2 and 3 consider log amounts of mortgages, consumer and C&I loans, respectively. Although the coefficients are negative, which is indicative of a reduction in lending, they are not statistically significant with the exception of consumer loans. While we find significant effects for consumer loans, these are economically insignificant with a reduction of nearly 0.12% nominally. These results suggest that the effect manifests itself within a bank largely in their liabilities rather than assets. Importantly, the banks we sample in the paper are relatively small, with nearly $100 million in total assets largely concentrated around lending. Our results may differ in the event of a large- to mid-sized bank (e.g. above $1 billion) sharing a name with a failed financial institution, as not only the bank run may be more severe given the larger network of depositors, but the diverse set of operations that are not typical in the smaller banks we study (e.g. asset management, securities trading, etc.) could result in hampered activities on the asset side.

5 The Model

To rationalize the empirical results and explore the mechanism, we build a model of financial contagion without fundamental linkages. The model is based on Diamond and Dybvig (1983) augmented to have two ex-ante identical banks, random investment returns, and noisy signals. A signal is considered noisy in the sense that it may represent one bank or another, depending on the degree of attention an investor pays. This attention, in turn, depends on the similarity of trademarks. Our interest is to show how a *good* bank can experience bank runs and how this effect is exacerbated by the similarity of trademarks. We will also examine the amplification through media coverage.

5.1 The Environment

The economy lasts for three periods: 0, 1 and 2. There are two locations indexed by $j = 1, 2$, and in each location, a unit measure of depositors indexed by $i \in [0, 1]$ enters the economy in period 0 with one unit of an endowment good. Depositors have a utility function $u(c_1 + \omega_i c_2)$, where $u(0) = 0$, $u'(0) = \infty$, $u' > 0$ and $u'' < 0$ and $\omega_i \in \{0, 1\}$ is a random variable. There is a probability π that $\omega_i = 0$ and the depositor is impatient, and a probability $1 - \pi$ that $\omega_i = 1$ and the depositor is patient. The type of a depositor is private information and is revealed at the beginning of period 1.

There is a single, constant-returns-to-scale technology for transforming this endowment into consumption in the later periods, which we call *project*. It delivers one unit of goods if liquidated in period 1. If it is instead held until period 2, it delivers R_z units of goods, where $z \in Z = \{b, g\}$. Let p_g denote the probability of the good return $R_g > R_b$, and the return is $R_b > 1$ with the complementary probability $p_b = (1 - p_g)$. The state z realizes at the beginning of period 1, and returns at each location are not correlated with each other.

The investment technology is operated at a central location in each location, where depositors pool and invest resources together in period 0 to insure individual liquidity uncertainty. This intermediation technology can be interpreted as a financial intermediary or *bank*, and thus, there are two banks in this economy. At the beginning of period 1, each depositor learns her type and either contacts the bank to withdraw funds in period 1 or waits until period 2 to withdraw. Depositors are isolated from each other in periods 1 and 2, and cannot engage in trade. Upon withdrawal, a depositor must immediately consume what is given. Repayments follow a *sequential service constraint* as in Wallace (1988). We also follow Ennis and Keister (2009) and prohibit the bank from pre-committing to actions so that a self-fulfilling bank run arises as an equilibrium outcome.[14]

Depositors may also condition their withdrawal decisions on a private signal about the asset returns. There are two signals, each of which corresponds to one of the realizations of the bank's asset return. However, a depositor can observe only one of them in period 1, and thus, the signal she receives may indicate the asset return of the other bank. A depositor cannot identify which

[14] Diamond and Dybvig (1983) examine how a suspension of convertibility can eliminate a bank run equilibrium, but Ennis and Keister (2009) show that such a policy is not time-consistent. We follow the latter approach to have a self-fulfilling bank run as an equilibrium phenomenon.

bank her received signal corresponds to. We let θ denote the probability of drawing the signal about the corresponding bank, and the value of θ is publicly known. Each signal itself is not noisy, and hence the depositor can correctly learn her bank's return if $\theta = 1$.

There are four states of the world: $\{(R_g, R_g), (R_g, R_b), (R_b, R_g), (R_b, R_b)\}$, where the first element represents the project return of Bank 1 and the second element expresses the project return of Bank 2. Since a depositor cannot tell whether her received signal corresponds to her bank or not when $\theta < 1$, she still has to worry about a potential bad state even in (R_g, R_g). Note that investment returns are independent between banks, and two banks do not have any interactions.

The sequence of events unfolds as follows. In period 0, the bank receives the endowment from its depositors and invests in the project. In period 1, the preference and the asset return are realized. A depositor receives a signal that may or may not represent her bank. After receiving the signal, depositors choose whether to withdraw their deposit in period 1 or in period 2. Finally, in period 2, the bank pays the remaining depositors.

5.2 Banking game

At each location, the bank and depositors play the simultaneous-move game. Depositors choose a contingent withdrawal plan at the same time the bank chooses the repayment schedule. Before a withdrawal action, depositor i observes a signal $\lambda^i \in \{b, g\}$, which influences their evaluation of expected payoffs. We thus solve a Bayesian Perfect Nash equilibrium consisting of depositor's posterior belief, depositors' withdrawal strategies, and the bank's withdrawal plan.

Posterior beliefs: When a depositor receives λ^i, the signal represents the investment return of her bank with probability θ. Let μ^{λ^i} denote the posterior belief that her bank has R_g if she receives signal λ^i, $\mu^{\lambda^i} \equiv Pr(g \mid \lambda^i)$. Using Bayes' rule, we have

$$\mu^g(\theta) \equiv Pr(g \mid g) = \theta + (1-\theta)p_g$$

and

$$\mu^b(\theta) \equiv Pr(g \mid b) = (1-\theta)p_g,$$

where $\mu^g(0) = \mu^b(0)$, $\partial\mu^g/\partial\theta > 0$, and $\partial\mu^b/\partial\theta < 0$. When θ is higher, a depositor believes that the signal is more likely to represent her bank and that her bank is more likely to have the return indicated by the signal. However, when $\theta < 1$, the depositor cannot distinguish which bank the signal corresponds to. Therefore, even in (R_g, R_g) or (R_b, R_b), the depositor still faces the uncertainty about the investment returns in period 1.

Withdrawal strategy: A depositor's withdrawal plan is conditioned on both her type and an extrinsic sunspot variable $s \in S = [0, 1]$ that is unobservable to the bank. We assume, without loss of generality, that the sunspot variable is uniformly distributed on $S \in [0, 1]$. A standard approach in the literature is to study under what conditions the following strategy profile constitutes an equilibrium.[15] Let $\hat{y}_i(\omega_i, s; q)$ denote a *cutoff strategy profile* such that

$$\hat{y}_i(\omega_i, s; q) = \begin{Bmatrix} \omega_i \\ 0 \end{Bmatrix} \text{ if } s \begin{Bmatrix} \geq \\ < \end{Bmatrix} q \text{ for some } q \in [0, 1], \forall i, \tag{2}$$

where $\hat{y}_i(\omega_i, s; q) = 0$ corresponds to withdrawal in period 1 and $\hat{y}_i(\omega_i, s; q) = 1$ corresponds to withdrawal in period 2. In this strategy profile, impatient depositors withdraw at period 1 and patient depositors withdraw in period 2 if the sunspot state is $s > q$, but both types of depositors withdraw in period 1 if the sunspot state $s \leq q$. Notice that, since s is uniformly distributed on $[0, 1]$, the value q can be interpreted as the probability of a run.

Repayment plan: The bank chooses a state-contingent repayment plan to maximize the expected utility of its depositors.[16] The first π depositors in the line of withdrawals receive a common amount c_1. If there is no run, there will be no more than π withdrawal requests in period 1. The bank will pay c_{2z}^N to the remaining depositors, where N denotes 'No run' and z represents the actual return. If there is a run, the bank still receives withdrawal requests after π withdrawals. Thus, the bank is able to infer whether a run is underway or not immediately after π withdrawals are made, and by this point of time, all uncertainty has been discerned. In case of a bank run, the bank pays c_{1z}^R to the remaining impatient depositors and c_{2z}^R to the remaining patient depositors.[17] Given q, the bank solves the following problem:

$$\max_{c_1, \{c_{1z}^N, c_{2z}^N, c_{2z}^R\}_{z=b,g}} \pi u(c_1) + \Sigma_z p_z \Big[(1-q)(1-\pi)u(c_{2z}^N) + q[\pi(1-\pi)u(c_{1z}^R) + (1-\pi)^2 u(c_{2z}^R)]\Big]$$

[15] See, for example, Cooper and Ross (1998), Peck and Shell (2003), and Ennis and Keister (2010).

[16] As is standard in the literature, the bank can be interpreted as a coalition of depositors or a representative bank with perfect competition in each location.

[17] This process can be interpreted as a bank resolution. Ennis and Keister (2009) explain the court intervention as an example.

subject to

$$
\begin{aligned}
(1-\pi)\frac{c_{2z}^N}{R_z} &= 1-\pi c_1, \\
\pi(1-\pi)c_{1z}^R + (1-\pi)^2\frac{c_{2z}^R}{R_z} &= 1-\pi c_1, \forall z,
\end{aligned}
$$

The first resource constraint represents the case of no bank run, or $s < q$, and the second constraint corresponds to the case of a bank run, or $s \geq q$. Under (2), all patient depositors run on the bank in case of a bank run, and hence, the measure of the remaining impatient depositors is $\pi(1-\pi)$. The measure of the remaining patient depositors is thus $(1-\pi)^2$. Letting η_z^N and η_z^R denote the Lagrangian multiplier on the first constraint and the second constraint in state z, respectively, the solution to the problem is characterized by the first-order conditions:

$$
\begin{aligned}
\eta_g^N + \eta_g^R + \eta_b^N + \eta_b^R &= u'(c_1), \\
\eta_z^N &= \mathbb{E}R_z u'(c_{2z}^N), \\
\eta_z^R &= u'(c_{1z}^R) = R_z u'(c_{2z}^R), \forall z.
\end{aligned}
$$

The last condition implies $c_{1z}^R < c_{2z}^R$. Assuming the CRRA utility function with the coefficient of relative risk aversion, γ, being greater than unity, we have

$$
\begin{aligned}
c_1^*(q) &= \frac{1}{\pi + \Omega(q)^{\frac{1}{\gamma}}} \\
c_{2z}^{N*}(q) &= \frac{R_z(1-\pi c_1^*(q))}{1-\pi} \\
c_{1z}^{R*}(q) &= \frac{(1-\pi c_1^*(q))}{\pi(1-\pi)+(1-\pi)^2 R_z^{\frac{1-\gamma}{\gamma}}} \\
c_{2z}^{R*}(q) &= c_{1z}^{R*}(q) R_z^{\frac{1}{\gamma}}, \forall z,
\end{aligned}
$$

where $\Omega(q) \equiv (1-q)(1-\pi)^\gamma\{\mathbb{E}R_z^{1-\gamma}\} + q\mathbb{E}\left[\pi(1-\pi)+(1-\pi)^2 R_z^{\frac{1-\gamma}{\gamma}}\right]^\gamma$. It is straightforward to show that $c_1^*(q) \leq \mathbb{E}c_{2z}^N(q), \forall q$, and c_1^* is decreasing in q while $\{c_{2z}^{N*}, c_{1z}^{R*}, c_{2z}^{R*}\}_{z=b,g}$ are increasing in q. If the crisis probability is high, the bank becomes more cautious and thus decreases the short-term repayment (c_1^*), which allows the bank to pay more in a later time. For the sake of exposition, we define $\beta_z = \frac{R_z^{\frac{1}{\gamma}}}{\left\{\pi(1-\pi)+(1-\pi)^2 R_z^{\frac{1-\gamma}{\gamma}}\right\}}$, where $\beta_z > 1, \forall z$. Then, we can express $c_{2z}^{R*} = \beta_z(1-\pi c_1^*)$.

5.3 Equilibrium bank runs

We now study when the strategy profile (2) constitutes an equilibrium. Because impatient depositors always choose to withdraw in period 1, it suffices to study the incentive of patient depositors. In particular, we study the expected payoffs of withdrawing in period 1 or 2 to guarantee that a patient depositor is willing to withdraw in period 2 if $s > q$ and in period 1 if $s \leq q$. When q is substantially large, the bank becomes cautious and reduces short-term payments, which in turn, discourages the depositor from running on the bank. We thus study the threshold of q such that a depositor is indifferent between withdrawing in periods 1 and 2, which implies the maximum probability of an equilibrium bank run. We use this maximum probability as the measure of fragility.[18]

We first characterize the expected payoffs. Suppose $s < q$. If a patient depositor arrives at the bank before π withdrawals, she will get c_1^*. Otherwise, she will receive c_{2z}^R. The depositor evaluates the state of the bank through the posterior belief. Let $v(y_i, q; \mu^z)$ denote the depositor's payoff when she chooses y_i and observe $\lambda^i = z$. Thus, the expected payoff of choosing to withdraw in period 1 is given by

$$\mathbb{E}v(0, q; \mu^z) = \pi u(c_1^*(q)) + (1 - \pi) \left\{ \mu^z u(c_{2z}^{R*}(q)) + (1 - \mu^z) u(c_{2z}^{R*}(q)) \right\}.$$

On the other hand, the expected payoff of withdrawing in period 2 is

$$\mathbb{E}v(1, q; \mu^z) = \mu^z u(c_{2z}^{R*}(q)) + (1 - \mu^z) u(c_{2z}^{R*}(q)).$$

When $\mathbb{E}v(0, q; \mu^z) \geq \mathbb{E}v(1, q; \mu^z)$, a depositor optimally runs on the bank. These expected payoffs satisfy the following properties.

Lemma 1 *If $\mathbb{E}v(0, q; \mu^z)$ and $\mathbb{E}v(1, q; \mu^z)$ cross each other, they satisfy the single-crossing property.*

This lemma guarantees that, if $\mathbb{E}v(0, q; \mu^z)$ and $\mathbb{E}v(1, q; \mu^z)$ cross each other, there exists the unique value of q such that $\mathbb{E}v(0, q; \mu^z) = \mathbb{E}v(1, q; \mu^z)$ holds, which we define as $\bar{q}$. The $\bar{q}$ is thus the maximum value of q such that profile (2) constitutes an equilibrium, which we use as the measure of fragility. If $\mathbb{E}v(0, q; \mu^z) \leq \mathbb{E}v(1, q; \mu^z)$ for any value of q, we define $\bar{q} = 1$. Likewise, if $\mathbb{E}v(0, q; \mu^z) \geq$

[18] This approach is based on the robust-control approach as in Gilboa and Schmeidler (1989) because $q = \bar{q}$ corresponds to the worst-case scenario, which has been applied in the sunspot approach to bank runs.

$\mathbb{E}v(1, q; \mu^z)$ for any value of q, we define $\bar{q} = 0$. When $\bar{q} \in (0, 1)$, the $\bar{q}$ is characterized by $\mathbb{E}v(0, \bar{q}; \mu^z) = \mathbb{E}v(1, \bar{q}; \mu^z)$, and by solving it, we have

$$\bar{q}(\theta, \lambda) = \frac{\Gamma(\mu^\lambda(\theta))^{\frac{\gamma}{\gamma-1}} - (1-\pi)^\gamma(\Sigma_z p_z R_z^{1-\gamma})}{\Sigma_z p_z \left\{\pi(1-\pi) + (1-\pi)^2 R_z^{\frac{1-\gamma}{\gamma}}\right\}^\gamma - (1-\pi)^\gamma \Sigma_z p_z R_z^{1-\gamma}}, \tag{3}$$

where $\Gamma(\mu^\lambda(\theta)) \equiv \mu^\lambda(\theta)\beta_g^{1-\gamma} + (1 - \mu^\lambda(\theta))\beta_b^{1-\gamma}$. Therefore, the value of θ influences the $\bar{q}$ through the posterior belief. If the signal is positive ($\lambda^i = g$), a depositor believes that her bank is more likely to have R_g, which in turn, motivates her to wait until period 2. If, instead, the signal is negative ($\lambda^i = b$), a depositor believes that her bank is more likely to have R_b, which in turn, incentivizes her to run on the bank. The following proposition formalizes these discussions.

Lemma 2 *The $\bar{q}(\theta, g)$ is decreasing in θ, and the $\bar{q}(\theta, b)$ is increasing in θ.*

For profile (2) to be part of equilibrium, we need $q \leq \bar{q}(\theta) \equiv \min\{\bar{q}(\theta, g), \bar{q}(\theta, b)\}$. Because $\mu^g(0) = \mu^b(0)$ and thus $\bar{q}(0, g) = \bar{q}(0, b)$, it is straightforward to show $\bar{q}(\theta, g) < \bar{q}(\theta, b)$, suggesting that the $\bar{q}(\theta)$ is implied by $\bar{q}(\theta, g)$. Thus, using the $\bar{q}(\theta)$, we characterize the trademark risk.

Proposition 1 *Fragility, measured by $\bar{q}(\theta)$, is decreasing in θ. The financial contagion through limited attention is measured by $\bar{q}(\theta) - \bar{q}(1)$, where $\theta < 1$; there is no contagion through limited attention when $\theta = 1$.*

The driving force of our results is how the private signal helps a depositor update their beliefs. If a signal is good, she believes that her bank is more likely to have R_g and has a smaller incentive to run on the bank. The value of θ introduces a noise here, which blunts her belief updating. Thus, a lower value of θ increases fragility.

5.4 Attention choices

We now turn our focus to an ex-ante attention allocation. We assume that θ is now chosen by each depositor through her ex-ante efforts. However, a depositor has to pay a cost $\delta C(\theta)$, where $\delta > 0$, $C(0) = 0$, and $C'(\theta) > 0$. Each of ex-ante identical depositors chooses θ in period 0 to maximize her expected utility by balancing the trade-off between leaving more resources and increasing the accuracy of her signal. We first characterize her expected utility by starting with the modified bank's problem. Taking θ as given, the bank now solves the following problem in period 1.

$$\begin{aligned} V(\theta,q) \equiv \max_{\{c_1,\{c_{1z}^N,c_{2z}^N,c_{2z}^R\}_{z=b,g}\}} \quad & \pi u(c_1(\theta)) + \Sigma_z p_z \Big[(1-q(\theta))(1-\pi)u(c_{2z}^N(\theta)) \\ & +q(\theta)(1-\pi)[\pi u(c_{1z}^R(\theta)) + (1-\pi)u(c_{2z}^R(\theta))]\Big] \end{aligned}$$

subject to

$$\begin{aligned} (1-\pi)\frac{c_{2z}^N(\theta)}{R_z} &= (1-\delta C(\theta)) - \pi c_{1z}(\theta), \\ \pi(1-\pi)c_{1z}^R(\theta) + (1-\pi)^2\frac{c_{2z}^R(\theta)}{R_z} &= (1-\delta C(\theta)) - \pi c_{1z}(\theta), \forall z. \end{aligned}$$

The solution to this problem differs from the previous section, but when the utility function is homothetic, such as the CRRA function, the chosen levels of consumption will be proportional to the ones in the previous section. We follow the same procedure as Section 5.3 to construct the $\bar{q}(\theta)$, and the expression of $\bar{q}$ is identical to (3) when the utility function follows the CRRA form. To capture changes in marginal run incentives, we evaluate $V(\theta,q)$ at $q=\bar{q}(\theta)$. In other words, a depositor chooses θ in period 0 by anticipating the worst-case equilibrium outcome. Assuming the CRRA function, we can rewrite $V(\theta,\bar{q}(\theta))$ as

$$V(\theta,\bar{q}(\theta)) = \frac{(1-\delta C(\theta))^{1-\gamma}}{1-\gamma}(\pi + \Omega\left(\bar{q}(\theta)\right)^{\gamma}$$

In period 0, a depositor solves the following problem

$$\max_{\theta\in[0,1]} V(\theta,\bar{q}(\theta)),$$

where a depositor chooses θ by considering its resource cost ($\delta C(\theta)$) and its effect on fragility. When θ is an interior solution, the optimal value of θ solves

$$\underbrace{\delta C'(\theta)\left\{\pi + \Omega(\bar{q}(\theta))\right\}}_{resource\ costs} = \underbrace{\frac{\gamma}{1-\gamma}(1-\delta C(\theta))\frac{\partial\Omega(\bar{q}(\theta))}{\partial\theta}}_{effects\ on\ fragility}, \tag{4}$$

The equation above expresses that a depositor balances the marginal benefit through $\bar{q}(\theta)$ with the resource cost.

When $\theta^* \in (0,1)$, the cost parameter δ determines the degree of attention. When δ is smaller, the depositor chooses a higher θ. When δ is instead larger, the depositor chooses a smaller θ. The following proposition summarizes the results.

Proposition 2 *The optimal attention is decreasing in* δ*.*

The value of δ can be interpreted in two ways. First, the δ itself is how similar banks' trademarks are. When two banks have very similar trademarks, depositors have to pay more attentions to details and be careful to distinguish information, which entails more costs. Thus, when banks have similar trademarks, depositors rationally choose to pay less attention, which in turn makes it easier for depositors to misidentify the signal, resulting in higher fragility. This mechanism explains our empirical results about financial contagion without fundamental linkage.

Corollary 1 *The trademark risk is represented by* $\frac{\partial \bar{q}(\theta^*)}{\partial \theta^*}\frac{\partial \theta^*}{\partial \delta}$ *and is increasing in* δ*.*

Second, we can also consider that the δ depends on investors' profiles. Institutional depositors likely need to exert less effort to monitor the lending situations of banks compared to retail depositors. If an institutional depositor is characterized by having a smaller δ than a retail depositor, our results suggest that banks with deposits predominantly from institutional depositors are less fragile than those reliant on retail depositors.

5.5 Media coverage

We extend our framework to have a public signal, which we call *media coverage*. When either bank or both banks draw a bad return (R_b), a public signal appears, and all depositors observe this signal in addition to their private signals. For example, under (R_g, R_g), this signal does not appear, which allows depositors to infer that all banks have R_g. However, under other combinations of returns, a depositor infers that her or the other bank has R_b. In such a case, the posterior belief is updated in the following way through Bayes' rule,

$$\mu_m^g(\theta) \equiv Pr(z = g \mid \lambda = g) = \theta$$

and

$$\mu_m^b(\theta) \equiv Pr(z = g \mid \lambda = b) = (1 - \theta)p_g,$$

where $\mu_m^g(\theta) \leq \mu^g(\theta)$ and $\mu_m^b(\theta) = \mu^b(\theta)$. When the private signal is bad, observing the (negative) public signal does not change the depositor's belief. However, when the private signal is good, observing the public signal erodes confidence. We use $\mu_m^\lambda(\theta)$ to evaluate the expected payoffs and derive $\bar{q}(\theta, \lambda)$. In particular, we replace $\mu^\lambda(\theta)$ with $\mu_m^\lambda(\theta)$ in (3), which we call $\bar{q}_m(\theta, \lambda)$. The

$\bar{q}_m(\theta, \lambda)$ has the same properties with $\bar{q}(\theta, \lambda)$, but its magnitude is different. By comparing them, we find the following relationship.

Lemma 3 *$\bar{q}_m(\theta, g) \begin{Bmatrix} = \\ > \end{Bmatrix} \bar{q}(\theta, g)$ if $\theta \begin{Bmatrix} = \\ < \end{Bmatrix} 1$, and $\bar{q}_m(\theta, b) = \bar{q}(\theta, b), \forall\theta$.*

Thus, when depositors pay enough effort such as $\theta = 1$, media coverage does not affect the fragility. However, when $\theta < 1$, media coverage can worsen fragility by allowing depositors to update their beliefs. Specifically, the difference $\bar{q}_m(\theta, \lambda) - \bar{q}(\theta, \lambda)$ captures the *media effect*:

Proposition 3 *Media coverage increases fragility by $\bar{q}_m(\theta, \lambda) - \bar{q}(\theta, \lambda)$, or*

$$\frac{\Gamma(\mu_m^\lambda(\theta))^{\frac{\gamma}{\gamma-1}} - \Gamma(\mu^\lambda(\theta))^{\frac{\gamma}{\gamma-1}}}{\Sigma_z p_z \left\{\pi(1-\pi) + (1-\pi)^2 R_z^{\frac{1-\gamma}{\gamma}}\right\}^\gamma - (1-\pi)^\gamma \Sigma_z p_z R_z^{1-\gamma}}. \tag{5}$$

The media effect is zero if $\lambda = b$ and positive if $\lambda = g$, and thus, the media effect appears when the fragility is measured by $\bar{q}(\theta, g)$, which suggests the following Corollary.

Corollary 2 *Media coverage amplifies fragility if and only if $\theta < 1$, and the magnitude of amplification is decreasing in θ.*

6 Conclusion

Our paper sheds light on trademark risk within the U.S. banking sector over the last two decades. By analysing the names of U.S. banking institutions, we observe a consistent decline since the 1990s in the number of banks with similar trademarks. Despite this trend, we find that approximately one in every five banks remains heavily exposed to trademark risk. When banking was primarily a local business, this exposure might not have posed a significant threat as it did not lead to confusion with other institutions. However, with the advent of the internet and branch banking, the potential for consumer confusion and the subsequent exposure to trademark risk has increased. Through difference-in-difference regressions, we show that sharing a trademark with a failed bank results in a 0.4% decrease in transaction deposits. This suggests that certain depositors exhibit a level of caution when faced with potential confusion or association with a failed bank.

Our findings are rationalized by exploring depositors' incentives when the similarity of trademarks increases the cost of distinguishing between banks. When it is costly for depositors to differentiate between banks, they choose to allocate less attention, resulting in less precise signals. In such a case, those who receive a good signal may still retain substantial doubts about their bank's asset quality, thus maintaining some incentive to run on the bank. This remaining uncertainty, or confusion, can escalate concerns among those who receive a bad signal, amplifying their incentive to run on the bank due to a perceived greater first-mover advantage. Thus, the similarity of trademarks creates a contagion channel through depositors' confusion even in the absence of fundamental linkages between banks.

The concept of "likelihood of confusion" in trademark law plays a crucial role in establishing trademark infringement or harm. With numerous banks sharing similar names, the potential for confusion among depositors regarding which bank is under distress can be of significant concern. Indeed, proving "likelihood of confusion" in courts can be an intricate and challenging task. We hope this paper motivates further research on measuring and mitigating the risks caused by shared names in the banking industry.

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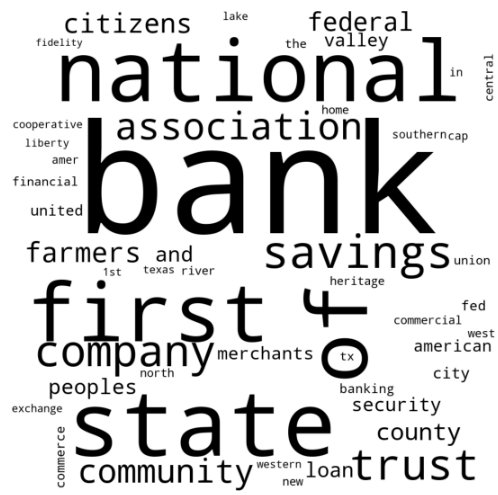
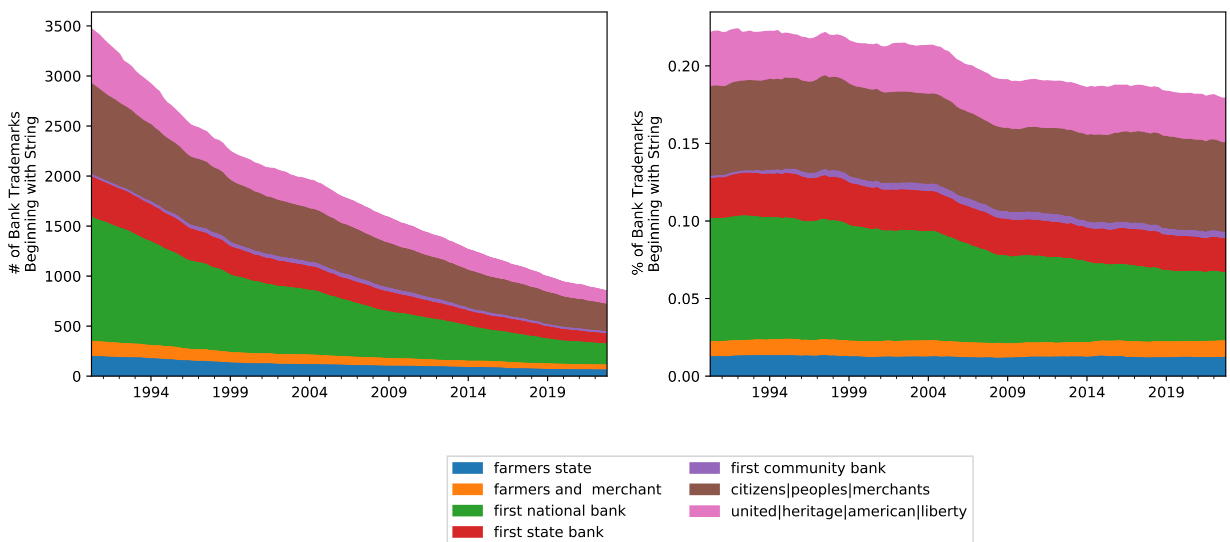
Figures

Figure 1: Common Words in Bank Names



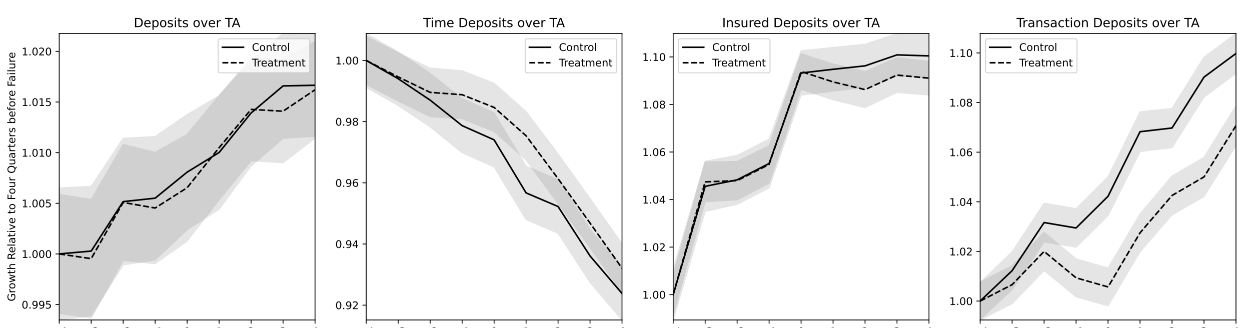
This figure shows frequency counts of bank names as of December 2022.

Figure 2: Bank Names Beginning with Common Strings



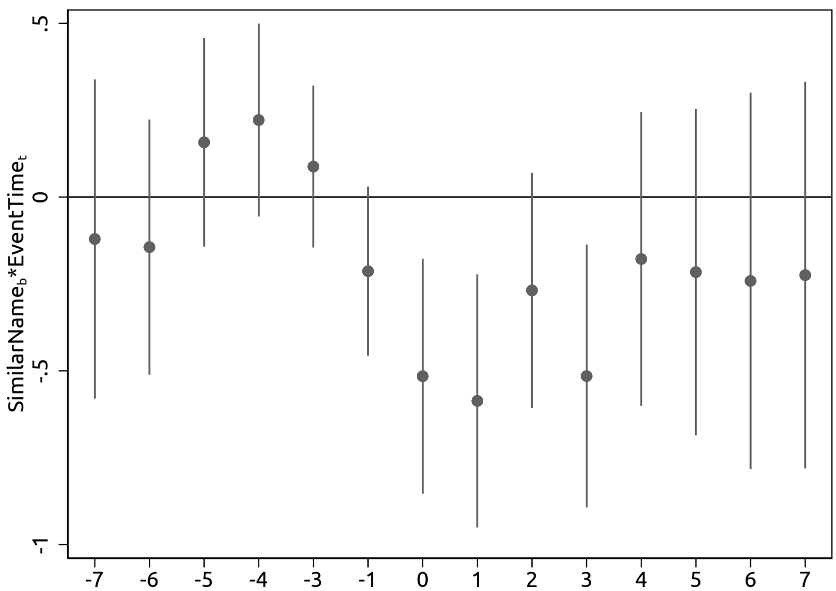
This figure shows how common bank names have evolved between 1990 and 2022. The left (right) chart shows the number (percentage) of banks that begin with a common string or phrase listed in the legend.

Figure 3: Pre-Trends and Impact



This figure shows the growth in various balance sheet variables of the banks in our sample relative to four quarters before the associated bank failure. Treatment banks are banks that share the name of a failed bank and Control banks are those that do not share their name but were matched during the propensity matching.

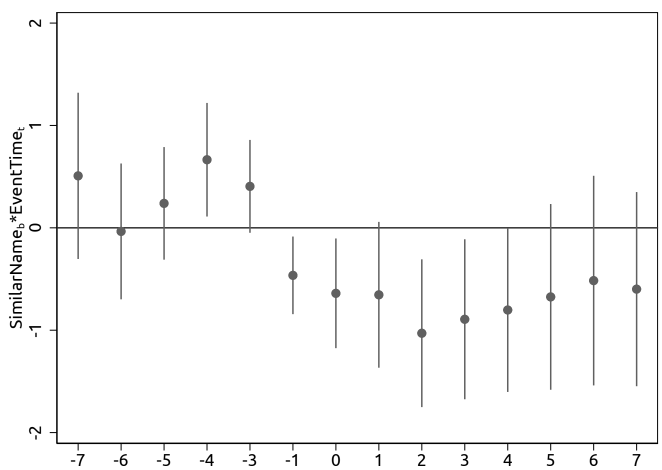
Figure 4: Regression Interaction over Time



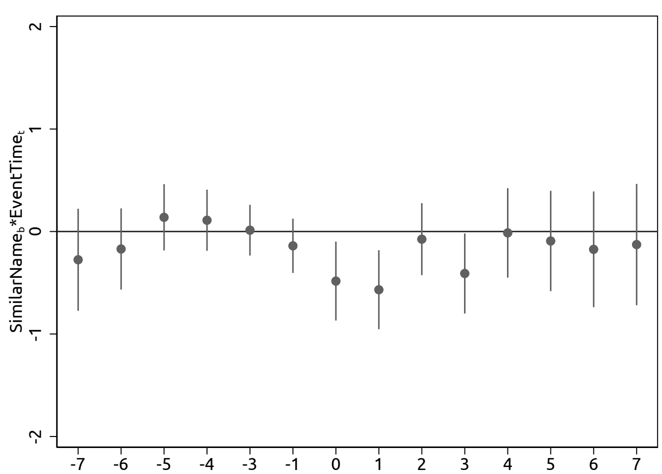
This figure shows the coefficients β_t resulting from the estimation of equation (1). Coefficients are displayed relative to event time equal to -2.

Figure 5: Media Exposure

(a) News Headline



(b) No Headline



This figure shows the coefficients β_t resulting from the estimation of equation (1) depending if the associated bank failure was featured in the news. Panel a (b) includes observations where the associated bank failure was (not) mentioned in a Reuters headline during the month of the failure. Coefficients are displayed relative to event time equal to -2.

Tables

Table 1: Bank Name Statistics as of December 2022

	(1)	(2)	(3)	(4)	(5)	(6)
	Treatment (899 Banks)			Control (894 Banks)		
Variable (2 Years Pre-Failure)	Mean	Std Dev.	Median	Mean	Std Dev.	Median
Time Deposits (over TA)	0.39	0.12	0.39	0.4	0.14	0.41
Transaction Deposits (over TA)	0.25	0.12	0.25	0.22	0.12	0.22
Uninsured Deposits (over TA)	0.01	0.05	0	0.01	0.05	0
Total Deposits (over TA)	0.83	0.1	0.85	0.84	0.1	0.86
Deposits over 250K (over TA)	0.16	0.08	0.15	0.15	0.09	0.15
Deposits under 250K (over TA)	0.23	0.09	0.22	0.24	0.1	0.25
Total Loans (over TA)	0.61	0.17	0.64	0.62	0.18	0.66
Mortgage Loans (over TA)	0.39	0.18	0.38	0.42	0.2	0.42
Consumer Loans (over TA)	0.05	0.05	0.04	0.05	0.05	0.04
C&I Loans (over TA)	0.09	0.06	0.08	0.09	0.06	0.07
ROA (%)	0.93	0.8	0.91	0.81	0.88	0.77
Log Assets	18.51	1.05	18.44	18.48	1.17	18.4

This table reports the summary statistics of the main variables used in the paper. Treatment banks are banks that share the name of a failed bank and Control banks are those that do not share their name but were matched during the propensity matching. This table was obtained by running a propensity score matching algorithm two years before the associated bank failure, matching on the logarithm of total assets, deposits to total assets, loans to total assets and profitability (proxied by ROA). The 107 bank failures from 2000 to 2022 considered for the study were obtained based on i) finding banks that match the name of the failed bank ii) at least two similarly named banks were identified iii) data available around the two-year window of the associated bank failure. All variables, except for Assets, are divided by total assets.

Table 2: Bank Name Statistics as of December 2022

	(1)	(2)	(3)	(4)
	Bank Name Starting with String		Bank Name Containing String	
	# of Banks	% of Banks	# of Banks	% of Banks
Word				
citizens	158	3.3%	171	3.6%
peoples	100	2.1%	104	2.2%
farmers	156	3.3%	177	3.7%
merchants	15	0.3%	73	1.5%
state	85	1.8%	863	18.1%
community	105	2.2%	259	5.4%
national	17	0.4%	760	16%
united	43	0.9%	54	1.1%
heritage	15	0.3%	28	0.6%
american	59	1.2%	63	1.3%
liberty	20	0.4%	22	0.5%
first	653	13.7%	711	14.9%
List of Words				
farmers state	56	1.2%	59	1.2%
farmers and merchant	50	1.1%	55	1.2%
first national bank	210	4.4%	216	4.5%
first state bank	103	2.2%	103	2.2%
first community bank	20	0.4%	20	0.4%
citizens—peoples—merchants	273	5.7%	347	7.3%
united—heritage—american—liberty	137	2.9%	164	3.4%

This table shows frequency counts of bank names as of December 2022. Columns 1 and 2 show the number and percentage of bank names that start with the associated string, respectively. Columns 3 and 4 show the number and percentage of banks that contain the associated string, respectively.

Table 3: Deposit Reaction to Bank Failures with Similar Names

	(1)	(2)	(3)
Dependent Variable	$TransactDep/TA_{b,t}$		
$SimilarName_b*AfterFailure_t$	-0.480***	-0.479***	-0.423**
	(0.172)	(0.170)	(0.167)
$AfterFailure_t$	0.961***	0.238	0.194
	(0.115)	(0.180)	(0.178)
$SimilarName_b$	0.0690	0.283	0.186
	(0.486)	(0.357)	(0.367)
Observations	12551	12551	12491
R-squared	0.948	0.954	0.955
Bank FE	Y	Y	Y
Quarter FE	N	Y	Y
Controls	N	N	Y

The dependent variable in columns 1 through 3 is the percentage of transaction deposits for each bank b during quarter t. The regressions incorporate the time period of three quarters around the time of failure for each failed bank. $SimilarName_b$ equals the value of one for banks that share the name of the associated failed bank and zero if not; $AfterFailure_t$ equals the value of one including and after the quarter of the associated bank failure, and zero otherwise, which leaves the period before the associated bank failure as the benchmark period (i.e., each estimated coefficient measures the differential effect after the associated bank failure to the period before associated bank failure). Fixed effects are either included ('Y') or not ('N'). Control variables include the lagged logarithm of total assets, lagged deposits to total assets, lagged loans to total assets and lagged profitability (proxied by ROA). Standard errors are clustered at the bank level and reported in parentheses (rounded to the third decimal). ***: Significant at 1% level; **: Significant at 5% level; *: Significant at 10% level.

Table 4: Robustness

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent Variable	$TransactDep/TA_{b,t}$						
	Only Treatment or Only Control	During GFC (2007-2010)	Excluding FNB	Excluding FSB	+/- 1 Quarter from Failure	Banking Demand Controls	$Log(TransactDep)_{b,t}$
$SimilarName_b$*$AfterFailure_t$	-0.383**	-0.415**	-0.466**	-0.327*	-0.337**	-0.449***	-0.0212**
	(0.167)	(0.194)	(0.198)	(0.195)	(0.156)	(0.171)	(0.00861)
$AfterFailure_t$	0.200	0.125	0.162	0.152	-0.0215	0.232	0.0123
	(0.178)	(0.191)	(0.203)	(0.285)	(0.190)	(0.184)	(0.00843)
$SimilarName_b$		-0.0840	-0.307	0.0187	-0.731	0.296	0.0330
		(0.564)	(0.556)	(0.475)	(0.487)	(0.381)	(0.0325)
Observations	11848	9768	8747	8670	5348	12239	12491
R-squared	0.960	0.963	0.949	0.959	0.967	0.954	0.986
Bank FE	Y	Y	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y	Y

The dependent variable in columns 1 through 6 is the percentage of transaction deposits for each bank b during quarter t. The dependent variable in column 7 is the logarithm of transaction deposit amount for each bank b during quarter t. The regressions incorporate the time period of three quarters around the time of failure for each failed bank. $SimilarName_b$ equals the value of one for banks that share the name of the associated failed bank and zero if not; $AfterFailure_t$ equals the value of one including and after the quarter of the associated bank failure, and zero otherwise, which leaves the period before the associated bank failure as the benchmark period (i.e., each estimated coefficient measures the differential effect after the associated bank failure to the period before associated bank failure). Column 1 restricts the sample to control banks that are never considered a treatment bank. Column 2 restricts the sample to bank failures that occurred between January 1, 2007 to December 31, 2010. Column 3 (and 4) omits the two associated treatment and control banks associated with the two (three) failures of First National (State) Bank. Column 5 restricts the sample to include the time period of one quarter around the time of failure. Column 6 controls for the average Tobin's Q and cash flows of all firms that exist in the headquarter of the bank to control for the demand for transaction deposits. Fixed effects are either included ('Y') or not ('N'). Control variables include the lagged logarithm of total assets, lagged deposits to total assets, lagged loans to total assets and lagged profitability (proxied by ROA). Standard errors are clustered at the bank level and reported in parentheses (rounded to the third decimal). ***: Significant at 1% level; **: Significant at 5% level; *: Significant at 10% level.

Table 5: Effect of Media Coverage

	(1)	(2)
Dependent Variable	$TransactDep/TA_{b,t}$	
	Reuters Headline	No Reuters Headline
$SimilarName_b$*$AfterFailure_t$	-0.780**	-0.342**
	(0.361)	(0.174)
$AfterFailure_t$	0.126	0.163
	(0.311)	(0.212)
$SimilarName_b$	3.414***	-0.0119
	(0.285)	(0.434)
Observations	2581	9910
R-squared	0.960	0.956
Bank FE	Y	Y
Quarter FE	Y	Y
Controls	Y	Y

The dependent variable in columns 1 and 2 is the percentage of transaction deposits for each bank b during quarter t. The regressions incorporate the time period of three quarters around the time of failure for each failed bank. $SimilarName_b$ equals the value of one for banks that share the name of the associated failed bank and zero if not; $AfterFailure_t$ equals the value of one including and after the quarter of the associated bank failure, and zero otherwise, which leaves the period before the associated bank failure as the benchmark period (i.e., each estimated coefficient measures the differential effect after the associated bank failure to the period before associated bank failure). Column 1 (2) includes observations where the associated bank failure was (not) referenced to in a Reuters headline during the month of the failure. Control variables include the lagged logarithm of total assets, lagged deposits to total assets, lagged loans to total assets and lagged profitability (proxied by ROA). Standard errors are clustered at the bank level and reported in parentheses (rounded to the third decimal). ***: Significant at 1% level; **: Significant at 5% level; *: Significant at 10% level.

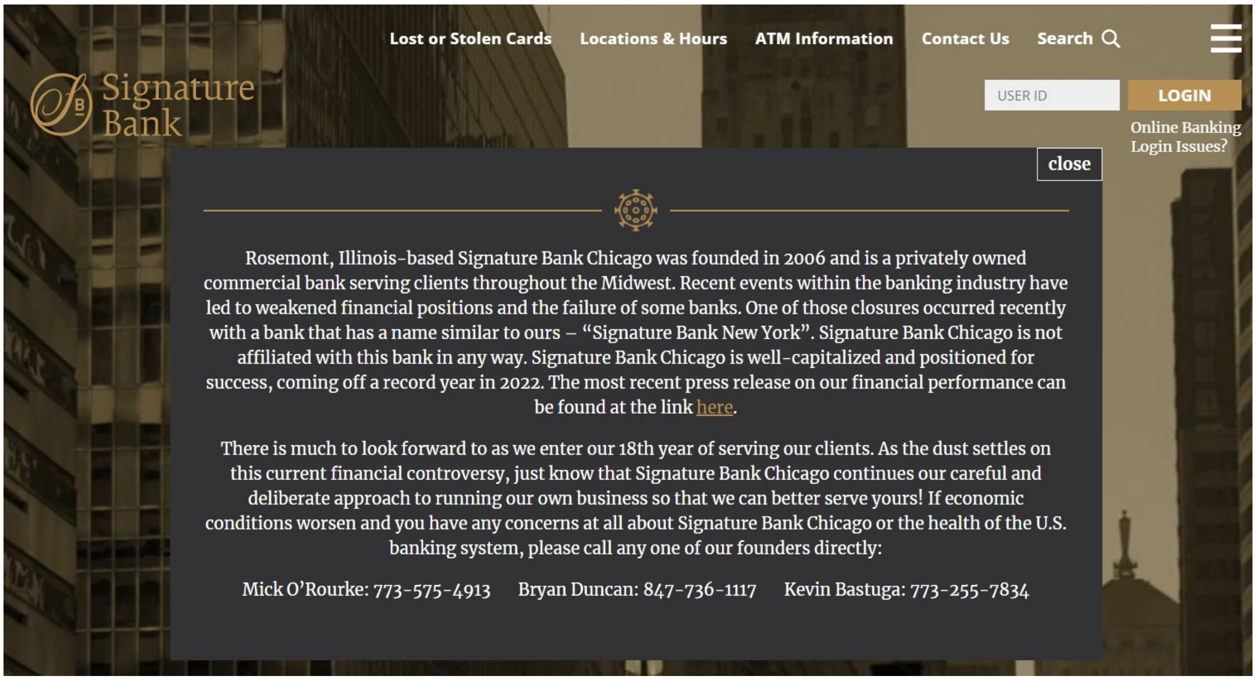
Table 6: Loan Variables

	(1)	(2)	(3)	(4)
Dependent Variable	$Log(Mortgages)_{b,t}$	$Log(Consumer)_{b,t}$	$Log(C\&I)_{b,t}$	$Log(Loans)_{b,t}$
$SimilarName_b$*$AfterFailure_t$	-0.0450	-0.121**	0.0141	-0.0134
	(0.178)	(0.0570)	(0.107)	(0.217)
$AfterFailure_t$	-0.00210	0.0888	-0.0488	0.129
	(0.169)	(0.0622)	(0.0941)	(0.211)
$SimilarName_b$	0.106	0.202	0.210	0.706
	(0.410)	(0.139)	(0.204)	(0.610)
Observations	12239	12239	12239	12239
R-squared	0.981	0.973	0.941	0.965
Bank FE	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y
Controls	Y	Y	Y	Y
Controls for Banking Demand	Y	Y	Y	Y

The dependent variables in columns 1 through 4 are the total mortgage, consumer, commercial industrial, and all loans over total assets, respectively. The regressions incorporate the time period of three quarters around the time of failure for each failed bank. $SimilarName_b$ equals the value of one for banks that share the name of the associated failed bank and zero if not; $AfterFailure_t$ equals the value of one including and after the quarter of the associated bank failure, and zero otherwise, which leaves the period before the associated bank failure as the benchmark period (i.e., each estimated coefficient measures the differential effect after the associated bank failure to the period before associated bank failure). Control variables include the lagged logarithm of total assets, lagged deposits to total assets, lagged loans to total assets and lagged profitability (proxied by ROA). Standard errors are clustered at the bank level and reported in parentheses (rounded to the third decimal). ***: Significant at 1% level; **: Significant at 5% level; *: Significant at 10% level.

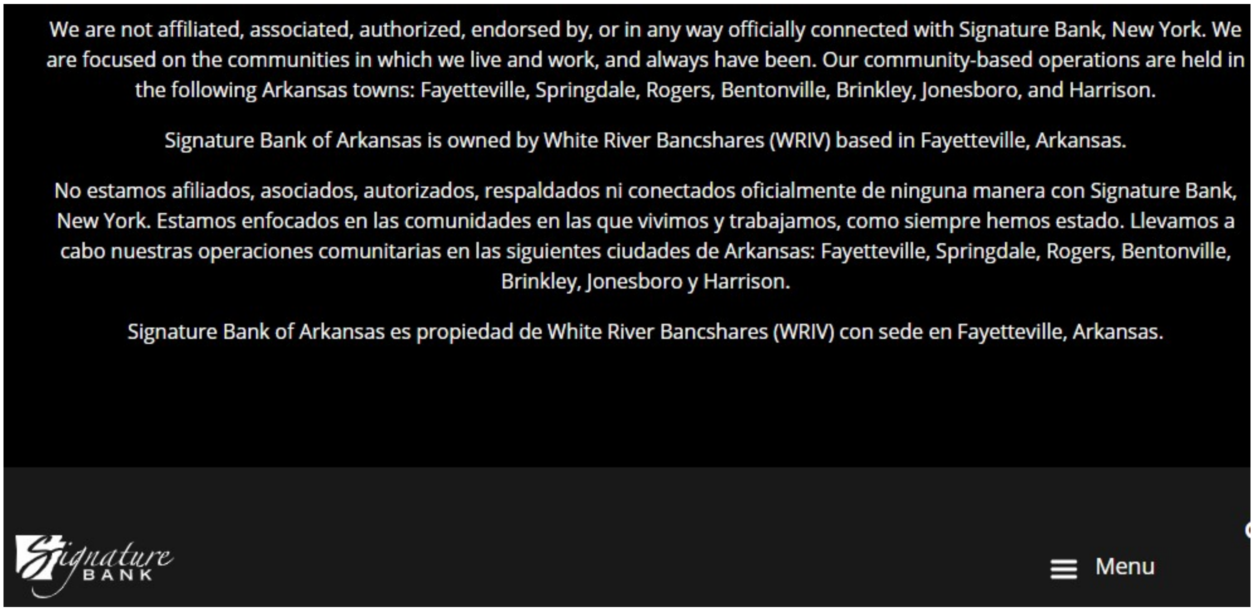
Appendix A

Figure 1: Signature Bank (Chicago) following Signature Bank (New York) Failure March 2023



This figure shows a snapshot of a public announcement by Signature Bank Illinois in response to the 2023 banking turmoil and the failure of Signature Bank New York.

Figure 2: Signature Bank (Arkansas) following Signature Bank (New York) Failure March 2023



This figure shows a snapshot of a public announcement by Signature Bank of Arkansas in response to the 2023 banking turmoil and the failure of Signature Bank New York.

Appendix B: Proofs

Proof of Lemma 1. We first differentiate $\mathbb{E}v(1, q; \mu^z, 1)$ with respect to q. Because $\partial c_{2z}^{R*}/\partial q > 0, \forall z$, we always have

$$\frac{\partial \mathbb{E}v(1, q; \mu^z)}{\partial q} = \mu^g u'(c_{2z}^{R*})\frac{\partial c_{2g}^{R*}}{\partial q} + (1-\mu^g)u'(c_{2z}^{R*})\frac{\partial c_{2b}^{R*}}{\partial q} > 0.$$

Notice that $\mathbb{E}v(0, q; \mu^z) = \pi u(c_1^*) + (1-\pi)\mathbb{E}v(1, q; \mu^z, 1)$ and $\partial u'(c_1^*)/\partial q < 0$, and then the following relationship always holds:

$$\frac{\partial \mathbb{E}v(1, q; \mu^z)}{\partial q} > \frac{\partial \mathbb{E}v(0, q; \mu^z)}{\partial q}.$$

Therefore, if $\mathbb{E}v(1, 0; \mu^z) < \mathbb{E}v(0, 0; \mu^z)$ and $\mathbb{E}v(1, 1; \mu^z) > \mathbb{E}v(0, 1; \mu^z)$, there exists the unique value of q such that $\mathbb{E}v(1, 0; \mu^z) = \mathbb{E}v(0, 0; \mu^z)$. Otherwise, they never cross each other. ■

Proof of Lemma 2. Differentiating $\bar{q}(\theta, \lambda)$, defined in (3), with respect to θ, we have

$$\frac{\partial \bar{q}(\theta, \lambda)}{\partial \theta} = \underbrace{\frac{\frac{\gamma}{\gamma-1}\Gamma(\mu^\lambda(\theta))^{\frac{1}{\gamma-1}}}{\Sigma_z p_z\left\{\pi(1-\pi) + (1-\pi)^2 R_z^{\frac{1-\gamma}{\gamma}}\right\}^\gamma - (1-\pi)^\gamma \Sigma_z p_z R_z^{1-\gamma}}}_{positive} \frac{\partial \Gamma(\mu^\lambda(\theta))}{\partial \theta},$$

and the sign of $\partial\Gamma(\mu^\lambda(\theta))/\partial\theta$ depends on λ. Specifically, the latter derivative is expressed as

$$\frac{\Gamma(\mu^\lambda(\theta))}{\partial \theta} = \underbrace{\left\{\beta_g^{1-\gamma} - \beta_b^{1-\gamma}\right\}}_{negative}\frac{\partial \mu^\lambda}{\partial \theta}$$

Given that $\partial\mu^g/\partial\theta > 0$ and $\partial\mu^b/\partial\theta < 0$, we have proven that the $\bar{q}(\theta, g)$ is decreasing in θ and the $\bar{q}(\theta, b)$ is increasing in θ, as desired. ■

Proof of Proposition 1. Since $\mu^g(0) = \mu^b(0)$, we have $\bar{q}(0, g) = \bar{q}(0, b)$. Lemma 2 implies that $\bar{q}(\theta, g) < \bar{q}(\theta, b)$ for any $\theta > 0$. Since $\bar{q}(\theta) = \min\{\bar{q}(\theta, g), \bar{q}(\theta, b)\}$, our measure of fragility, the $\bar{q}(\theta)$, is determined by $\bar{q}(\theta, g)$, which is decreasing in θ. ■

Proof of Proposition 2. Suppose the first order condition (4) characterizes the optimal level of θ. Differentiating (4) with respect to δ, we obtain

$$\frac{\partial \theta^*}{\partial \delta} = \frac{\overbrace{C'(\theta^*)(\pi + \Gamma^{\frac{\gamma}{\gamma-1}}) + \frac{\gamma}{1-\gamma}C(\theta^*)(1-p_g)\Theta\frac{\gamma}{\gamma-1}\Gamma(\theta^*)^{\frac{1}{\gamma-1}}}^{positive}}{\underbrace{\frac{\gamma\Theta\Gamma(\theta^*)^{\frac{1}{\gamma-1}}}{(\gamma-1)^2}(1-p_g)\left[\delta C'(\theta) + \frac{\gamma\Theta\Gamma(\theta^*)^{-1}}{1-\gamma}\left(1-\delta C(\theta^*)\right)(1-p_g)\right] - \delta C'(\theta^*)(\pi + \Gamma(\theta^*)^{\frac{\gamma}{\gamma-1}})}_{negative}} < 0,$$

where $\Theta \equiv \beta_g^{1-\gamma} - \beta_b^{1-\gamma} < 0$. Note that, because $\gamma > 1$, each term in the numerator is positive and that each term in the denominator is negative. Therefore, the optimal level of attension (θ^*) is decreasing in δ. ■

Proof of Corollary 1. This result is implied by Propositions 1 and 2. ■

Proof of Lemma 3. The difference between $\bar{q}_m(\theta,\lambda)$ and $\bar{q}(\theta,\lambda)$ comes from the difference between $\mu_m^\lambda(\theta)$ and $\mu^\lambda(\theta)$. Because $\mu_m^\lambda(\theta) = \mu^\lambda(\theta)$, we have $\bar{q}_m(\theta,b) = \bar{q}(\theta,b)$. When $\lambda = g$, we have $\bar{q}_m(\theta,g) \geq \bar{q}(\theta,g)$ because $\mu_m^g(\theta) \geq \mu^g(\theta)$ and the equality holds if and only if $\theta = 1$. ■

Proof of Proposition 3. Recall that the $\bar{q}(\theta,\lambda)$ is defined by

$$\bar{q}(\theta,\lambda) = \frac{\Gamma(\mu^\lambda(\theta))^{\frac{\gamma}{\gamma-1}} - (1-\pi)^\gamma(\Sigma_z p_z R_z^{1-\gamma})}{\Sigma_z p_z \left\{\pi(1-\pi) + (1-\pi)^2 R_z^{\frac{1-\gamma}{\gamma}}\right\}^\gamma - (1-\pi)^\gamma \Sigma_z p_z R_z^{1-\gamma}}, \tag{6}$$

and the $\bar{q}_m(\theta,\lambda)$ is defined by

$$\bar{q}_m(\theta,\lambda) = \frac{\Gamma(\mu_m^\lambda(\theta))^{\frac{\gamma}{\gamma-1}} - (1-\pi)^\gamma(\Sigma_z p_z R_z^{1-\gamma})}{\Sigma_z p_z \left\{\pi(1-\pi) + (1-\pi)^2 R_z^{\frac{1-\gamma}{\gamma}}\right\}^\gamma - (1-\pi)^\gamma \Sigma_z p_z R_z^{1-\gamma}}. \tag{7}$$

Lemma 3 implies $\bar{q}_m(\theta,\lambda) - \bar{q}(\theta,\lambda) \geq 0$, and the difference can be rewritten as (5). ■

Proof of Corollary 2. The only difference between $\bar{q}_m(\theta,\lambda)$ and $\bar{q}(\theta,\lambda)$ is the first term in the numerator. In (5), $\left(\mu^\lambda(\theta) - \mu_m^\lambda(\theta)\right)$ is decreasing in θ and is zero when $\theta = 1$. Thus, the amplification through media coverage is decreasing in θ and disappears when $\theta = 0$. ■