Worried Depositors

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Abstract

Depositors' risk perceptions are a key source of bank fragility and discipline in theory, but direct evidence is scarce. We propose a strategy to measure these perceptions and separate their effects on banks from underlying fundamentals. We proxy for risk perceptions by tracking abnormal online search volumes about banks. We show that perceptions deteriorate with negative public signals about banks, and that banks offer higher deposit rates in response. Exploiting variation in perceptions of different brands of the same bank, we find that part of this response cannot be explained by fundamentals. Comparing onshore on offshore deposits within the same brand and time period, we show that banks' response is stronger for uninsured deposits.

Keywords: Banks; brands; deposits; information acquisition; deposit insurance.

JEL Codes: G21; G32.

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Traditional commercial banks issue demandable deposits and hold risky assets whose value is opaque to outsiders (Dang et al., 2017). This business model has two well-known corollaries. First, banks are exposed to early withdrawals by depositors worried about banks' safety. Second, depositors' withdrawal decisions are not based on bank-specific fundamentals but on noisy signals, aggregate information, or expectations about other depositors' behaviour (Diamond and Dybvig, 1983; Gorton, 1988; Goldstein and Pauzner, 2005).

Together, these theories suggest that shifts in depositors' risk perceptions can be a significant source of discipline and fragility for banks. Importantly, this should be true regardless of the extent to which perceptions deviate from underlying fundamentals, for instance when depositors are ill-informed about banks or unaware of deposit insurance. The main objective of this paper is to test this idea empirically.[1]

More specifically, we seek to evaluate three untested theoretical predictions. First, depositors' risk perceptions deteriorate with negative public signals about banks (Goldstein and Pauzner, 2005). Second, deteriorating perceptions increase the risk of withdrawals in times of aggregate stress, compelling banks to raise deposit rates and thus erode their profitability (Egan et al., 2017). Third, this effect should be stronger without deposit insurance (Egan et al., 2017)

The absence of direct evidence on these issues might reflect three challenges: measuring latent factors such as perceptions; isolating their effects from those of underlying fundamentals; and obtaining plausibly exogenous variation in the availability of deposit insurance.

We address these challenges with three innovations. First, we proxy for changes in depositors' risk perceptions by tracking abnormal online information gathering about banks, in line

[1]Following Gorton (1988) we use "perceptions" to refer to depositors' assessment of deposit risk on the basis of information available to them. Typically, this assessment can differ from other agents' because depositors (or a subset thereof) can only observe noisy signal of fundamentals (Goldstein and Pauzner, 2005). Other terms have been used to refer to the same concept, such as beliefs (Diamond and Dybvig, 1983), fears (Chari and Jagannathan, 1988), expectations (Matutes and Vives, 2000) or worries (He and Manela, 2016). Anecdotally, authorities such as the UK Financial Conduct Authority (2009) judged that the low public awareness of deposit insurance could "increas[e] the likelihood of a run on a deposit taker" and adopted new regulations to address this issue, suggesting material concerns about unsubstantiated risk perceptions.

with models where depositors receiving a negative signal about a bank acquire more information about this bank before deciding to stay or run (He and Manela, 2016; Ahnert and Kakhbod, 2017; Schliephake and Shapiro, 2018). Second, we exploit the fact that most large UK banks use multiple deposit-taking brands. Since they are not legally separate entities, brands are irrelevant for the risk faced by a depositor. But since depositors tend to be primarily familiar with brands rather than their parent bank, perceptions of this risk can vary across brands. This discrepancy allows us to estimate banks' response to abnormal searches for brands while controlling for fundamentals via bank-time fixed effects. Third, we exploit the fact most UK banks offer the same deposit products both in the UK and in the British Crown Dependencies ("offshore"). Since Dependencies introduced deposit insurance at different times in the sample period, we can test how the rate for the same product offered by the same brand and in the same week responds to abnormal information acquisition depending on deposit insurance.

We find evidence consistent with the three theoretical predictions above. First, abnormal online searches for banks increase with negative signals about banks in newspapers and financial markets. Second, banks faced with higher increases in abnormal searches during the 2007-2009 financial crisis offer higher rates on deposits that can be withdrawn without notice. This suggests that banks respond to declining depositors' risk perceptions by increasing the cost of withdrawals, consistent with a motive to retain worried depositors. This result is consistent with evidence that US banks 'scrambled for deposits' during the crisis by offering higher deposit rates (Acharya and Mora, 2015). However our result is robust to including bank-week fixed effects, suggesting that perceptions matter over and above fundamentals in that context. Third, the response to declining risk perceptions is larger for deposits and time periods without deposit insurance - particularly so for banks more exposed to funding liquidity risk - consistent with the idea that uninsured depositors face a larger potential loss in the event of a bank default.

We begin our study by motivating our usage of Google search volume data to proxy for changes in depositors' risk perceptions. In addition to theories where declines in risk perceptions coincide with increased information gathering about banks (He and Manela, 2016), this approach exploits the fact that a substantial share of information acquisition in the modern context is likely to take place online. Consistent with this idea, Google search data has been found to capture the public's concerns about stock returns, unemployment, or health issues, among others (Preis et al., 2013; Da et al., 2014; Mellon, 2013; Althouse et al., 2014). A key advantage of Google data is that it can capture situations in which withdrawals become more likely, without necessarily materializing yet.[2] In addition, the data is representative and granular enough to measure the public's concerns about specific banks within narrow time periods.[3]

In order to filter out searches unrelated to bank risk (e.g. searches for a bank's branch location or website), we follow Da et al. (2011) and create a measure of *Abnormal Searches*. We document two main findings supporting our usage of this data. First, surges in *Abnormal Searches* about a bank are associated with deposit outflows from this bank, and this effect is only significant for deposits held by individuals, as opposed to those held by companies or banks. Second, using a panel vector auto-regressive model, we show that *Abnormal Searches* increase with public signals about banks in newspapers (as measured by an index of negative coverage of banks in UK newspaper in the spirit of Soo (2018)) and in financial markets (as measured by CDS spreads). In contrast CDS spreads and media coverage do not respond to increased *Abnormal Searches*, consistent with the notion that retail depositors respond with a lag relative to other (presumably better informed) agents (Schliephake and Shapiro, 2018).

The finding that *Abnormal Searches* is correlated with negative media coverage, CDS prices, and deposit outflows supports our usage of this variable as proxy for changes in depositors' risk

[2] Preis et al. (2013) argue that search volumes predict stock market drops since these drops "are preceded by periods of investor concern. In such periods, investors may search for more information (...) before eventually deciding to buy or sell." By the same logic, online searches for the term "unemployment" reveals individuals' concerns about future job losses to an extent that actual unemployment data cannot (Da et al., 2014).

[3] Google has consistently ranked first in terms of search engines, with a global market share close to 90%. (Source: Jumpshot's clickstream data)

perceptions. Since these correlates might also affect deposit rates, however, the key identification challenge we face is to disentangle banks' response to changes in risk perceptions from that to these factors.

Our strategy to separate these effects exploits the fact that most large UK banks use multiple brands. For instance, HSBC offers similar retail deposits under both the HSBC and First Direct brands. Since banks use differentiated marketing for each brand, UK depositors tend to be primarily familiar with brand names, without necessarily knowing their parent company. Consistent with this idea, UK authorities introduced new legislation that forced banks to advertise their entire brand portfolio and group structure to new depositors from 2011. This suggests that, before this point, depositors' risk perceptions can vary across brands of a same bank. For instance, negative news about HSBC can affect the risk perceptions of HSBC-brand depositors, but not necessarily those of First Direct depositors. In line with this, the Competition and Markets Authority (2016) noted that, albeit owned by the RBS Group, the NatWest brand was less "readily associated by customers with the negative media coverage received by [RBS] during and after the financial crisis".

Unlike depositors' perception thereof, the riskiness of a bank cannot vary across brands of a same bank. This is because, unlike subsidiaries within a group, brands are not legally separate entities within a bank and are thus backed by the same balance sheet. Therefore, brands are irrelevant for the risk faced by a depositor. By the same token, brands are irrelevant for the value of a deposit to the bank. This unique setting allows us to estimate the relationship between deposit rates for a bank or brand (for multiple-brand banks) and abnormal information acquisition about this bank/brand, while controlling for fundamental determinants of deposit rates with bank-week fixed effects.[4]

[4] In spirit, this identification is the mirror image of Drechsler et al. (2017). The authors investigate the deposit market power of US banks by comparing deposit rates across different branches of the same bank, while controlling for bank-time fixed effects. This identification would not suit the UK context because the UK retail deposit market is fully integrated geographically - that is, there is no variation in deposit rates by a same bank

To do so, we collect weekly data on deposit rates for all deposit products offered by UK banks between 2007 and 2015. Using detailed information on account characteristics, we classify each deposit into one of approximately 150 unique product categories. This allows us to additionally control for time-varying shifts in depositors' preferences with product-week fixed effects.

Our results suggest that banks offer higher deposit rates when depositors' perceptions towards a bank or brand deteriorate. The magnitude of this response decreases when including bank-week and product-week fixed effects, but it remains significant to a 1% confidence level. Therefore, a significant part of banks' response cannot be explained by bank-level or aggregate fundamentals. In line with the idea that banks attempt to increase the cost to worried depositors of withdrawing, the link between *Abnormal Searches* and deposit rates is only significant for deposits that can be withdrawn without notice, as opposed to deposits with limits or penalties on withdrawals. Consistent with depositors being more prone to withdraw in periods of aggregate uncertainty (Artavanis et al., 2019), the relationship between *Abnormal Searches* and deposit rates is only significant during the global financial crisis period (September 2007 to November 2009). And consistent with the cost of potential withdrawals increasing with their size, the response of deposit rates to abnormal searches is approximately 80% higher for accounts with a £100,000-minimum deposit, relative to that for accounts with a £10,000-minimum deposit.

This last result suggests a possible role for deposit insurance. In particular, deposit insurance reduces the potential loss that a depositor faces in case of a bank default. Therefore, banks might need to respond more strongly to declining risk perceptions when deposits are not insured, particularly so for banks with a higher probability of default. We test this idea in the final part of the paper. To do so we compare how the deposit rate for the same UK brand and time period responds to increased abnormal searches for this brand depending on whether the

across different regions (except potentially in Scotland, which is not covered in our sample).

deposit is offered in an offshore jurisdiction and time period without deposit insurance. Importantly the British Crown Dependencies (Jersey, Guernsey, and the Isle of Man) introduced deposit insurance in a staggered way between 2008 and 2010. We can thus perform this test controlling for unobserved time-varying heterogeneities across jurisdictions and depositor clienteles, such as heterogeneities in average wealth or sophistication.

Consistent with our prior, we find that the deposit rates response to *Abnormal Searches* is more than twice larger without deposit insurance. This effect is even stronger for banks more exposed to funding liquidity risk. These results are robust to including both brand-product-week fixed effects and offshore-week fixed effects, suggesting that self-selection of heterogeneous depositor clienteles across jurisdictions and confounding fundamental determinants of bank risk do not explain this result.

In summary, we make three contributions to the existing literature. First, to the best of our knowledge, ours is the first paper to isolate and quantify the role of depositors' riskier perceptions as a source of discipline and potential bank fragility in the modern context.[5] An extensive number of studies including Acharya and Mora (2015) test whether riskier banks are disciplined through higher deposit rates, but do not disentangle between the effects of changes in risk from those in depositors' perception thereof.[6] Our results complement evidence that, in normal times, insured depositors are insensitive to bank risk (Hanson et al., 2015) and riskier banks do not offer higher deposit rates (Ben-David et al., 2017). We find that in times of elevated systemic risk, banks are 'punished' through higher deposit rates if they face deteriorating risk perceptions in such circumstances.

Second, another set of studies analyse the motives for deposits' decision to withdraw during

[5] Gorton (1988) finds that runs during the U.S. National Banking Era (1863-1914) were more likely when the aggregate currency-to-deposit ratio exceeded a critical value. The author attributes this finding to depositors' perceptions changing with new information suggestive of increased recession risk.

[6] Analyses of the relationship between accounting-based bank risk measures and deposit rates include: Hannan and Hanweck (1988); Avery et al. (1988); Gorton and Santomero (1990); Cook and Spellman (1994); Flannery and Sorescu (1996); Park and Peristiani (1998); Martinez Peria and Schmukler (2001); Cubillas et al. (2012).

crises episodes, with a particular focus on separating panic-based from fundamental determinants.[7] We add to this research by documenting how banks react to changes in the probability of withdrawals associated with declining depositors perceptions. This complements evidence that depositors' withdrawal decisions are sensitive to deposit rates during the Greek crisis (Artavanis et al., 2019).

Third, our paper contributes to a recent literature that highlights the role of banks' retail deposit franchise as a source of funding stability in normal times (Egan et al., 2017; Drechsler et al., 2017). Our findings suggest that consumer differentiation across deposit brands can also have negative implications for banks' profitability under stress circumstances.

1 Data and Samples

We focus our study on the UK for three key reasons. First, the UK banking system is large and underwent a severe shock in 2007-2008 with the run on Northern Rock, the bailout of two major banks (Lloyds and RBS), and the collapse of UK branches of Icelandic banks.[8] This allows us to study both a crisis period and its relatively calmer aftermath. Second, the fact that the largest UK banks offer similar deposits under different brands allows us to study the banks' response to depositors' perceptions while controlling for changes in these banks' fundamentals. Third, the peculiar relationship between the UK and the British Crown Dependencies provides variation in deposit insurance across time and jurisdictions; this allows us to study how deposit insurance affects banks' response to shifts in depositors' perceptions.

[7] Kelly and O Grada (2000), Iyer and Puri (2012), Iyer et al. (2016), Iyer et al. (2018), and Martin et al. (2018) study individual depositors' behaviour. Less granular studies include: Gorton (1988); Saunders and Wilson (1996); Calomiris and Mason (1997); Billett et al. (1998); Goldberg and Hudgins (2002); Hasan et al. (2013); Davenport and McDill (2006); Bennett et al. (2015); Lamers et al. (2015); and Brown et al. (2017).

[8] By 2014, UK financial institutions' assets amounted to 13 trillion (20 trillion including derivatives), 61% of which were held by commercial banks and building societies. Like US savings and loans, building societies focus mainly on deposit-taking and mortgage lending. UK banks and other financial institutions' 2014 total assets amounted to about twelve times UK's GDP, compared to five for France and seven for Japan (Burrows et al., 2015).

1.1 Data

We collect data from six main sources.

Deposit Rates First, we assemble a novel database of rates offered by UK banks on a range of deposit products. This data is collected daily by the Moneyfacts Group and published on its website and monthly magazine. The raw dataset we obtained covers rates for 41,588 unique deposit products offered by UK banks between January 2007 and August 2015. The advertised rates are valid for all regions in England and Wales. That is, unlike in the US deposit market, there are no regional differences in deposit rates within banks.

For each deposit product, Moneyfacts reports rates for deposits with up to seven minimum balance amounts: £1,000, £5,000, £10,000, £25,000, £50,000, £100,000, and £125,000. The data also reports the following product characteristics: product type (savings account, current account, etc.), interest-rate type (variable or fixed), interest-rate payment frequency, term (sight, time, etc.), withdrawal-notice requirements, and access type (branch, or internet/telephone-only). We combine these characteristics to group each deposit into a unique deposit category, allowing us to trace similar products across time and compare rates for products within each category across banks. The most common deposit type in our sample is a variable-rate, sight, current account with annual interest payment, no withdrawal notice, and branch access. Since other key variables used in our tests have a weekly frequency, we use rates posted on Mondays. Because our focus is on studying whether banks respond to deteriorating perceptions by making withdrawals more costly to existing depositors, we focus on variable-rate deposits. In addition, we exclude deposits in currencies other than British pounds in order to mitigate any bias from exchange rate differentials.

We also exclude two groups of banks present in the Moneyfacts data. First we drop foreign or foreign-owned banks as well as non-banks (such as the deposit-taking operations of supermarket chains) since we don't have access to consolidated balance sheet data for these entities. If a bank is acquired by a foreign bank or a non-bank during our sample period, we drop it from our sample following the event. Second, we eliminate the smallest building societies – those with less than 15 branches – since Google Trends data is less accurate for terms with low average search volume. After these screenings, our Moneyfacts data includes 150 deposit-product categories offered under 42 different brands by 26 different banks.

Google Searches Second, we collect data for online search volumes for the name of each UK bank and brand, obtained from the Google Trends website. The data is available at daily, weekly or monthly frequency depending on search volumes. For instance, daily data is available for common search terms like "HSBC", but data for less usual combinations like "Skipton Building Society" is only available at the weekly frequency. We thus use weekly data for our main tests in order to be able to include a larger number of banks. We choose search terms that unambiguously refer to a bank's brand. For instance, we retrieve search volumes for "Derbyshire Building Society" and not for "Derbyshire", since the latter could be used to search information on the Derbyshire county. The data is normalized by Google over the 0-100 interval, with 100 corresponding to the maximum "search query share" during that period. The query share is defined as the ratio of searches for a given term relative to all searches during a same time period. Therefore, Google Trends data provides a measure of relative search popularity. Since the raw data is normalized to zero when search volume falls below a minimum threshold, we drop observations for which the present or any of the 8 lags of search volume are equal to zero in order to minimize measurement error.

Newspaper Coverage Third, we obtain all the newspaper articles that mention a UK bank or brand name between 2007 and 2015 from Factiva. We discard articles evidently not related to banking; for instance, we drop football-related articles that mention Barclays bank in its role of sponsor of the Premier League.

Deposit Balances Our fourth source of information is a confidential Bank of England database that contains detailed monthly information on aggregate deposit balances. The list of banks included is updated regularly in order for the data to cover at least 75% of UK aggregate deposits. Therefore, the largest UK banks are continuously included, but the coverage of smaller banks changes over time. The data reports deposit balances for 49 categories of depositors or depositor-type-maturity combinations. For our analysis, we study deposit balances across the following sectors: individuals; public non-financial firms; and financial firms.

Bank Balance Sheets and CDS spreads Our fifth database comprises quarterly filings by all UK banks regulated by the Bank of England's Prudential Regulation Authority (PRA). We use this data to create the following bank-level control variables: retail funding (deposits held by UK individuals over total liabilities);[9] cash (cash holdings over total assets); capital (Tier 1 capital as a fraction of total assets); provisions (flow and stock of provisions for impairments over total assets); loans to banks, insurance companies, and mortgages (each measured as fraction of total loans); and size (logarithm of total assets). Following Ben-Rephael et al. (2017) we additionally construct a proxy for a bank's investment opportunities by computing quarterly changes in the logarithm of total assets. Table 1 reports complete definitions and data sources. Finally, our sixth source of data consists in weekly CDS spreads for the largest UK banks, obtained from the Bloomberg database.

1.2 Samples Construction

We combine the data described above into three different datasets.

[9] The data does not allow us to include deposits by non-UK individuals in our measure.

Deposit Balances Dataset Our first dataset starts from Bank of England deposit balances data. Because this data is monthly and does not distinguish between the different brands of multiple-brand banks, we merge it with monthly Google search volume data for the name of UK banks. The final dataset varies by bank, month, and depositor type, and covers a subset of larger UK banks. We use this data to validate our choice of online search volumes as a proxy for depositors' risk perceptions in Section 2.

Deposit Rates Dataset Our second dataset starts with the weekly Moneyfacts deposit rates data for all onshore deposit products, and combines it with weekly Google search volumes for names of banks (or brands for multiple-brand banks). This dataset varies by bank or brand (for multiple-brand banks), week, and deposit product, and covers all UK banks. We use this dataset in order to estimates banks' response to shifts in depositors' perceptions (Section 3).

Offshore/Onshore Dataset' Our third dataset augments the Deposit Rates Dataset with offshore deposits offered by banks included in the latter dataset. We use this dataset to identify how deposit insurance affects banks' response to depositors' perceptions in Section 4.

We provide a list of the banks and brands included the Deposit Rates Dataset in Table 2. Column 1 reports the name of banks or this banks' main brand for multiple-brand banks, and column 2 reports the names of secondary brands of multiple-brand banks.[10] The subset of banks included in the Deposit Balances Dataset are marked with a † superscript. Finally we indicate the banks or brands that offer offshore products included in the "Offshore/Onshore Dataset" with a * superscript. All datasets span the 2007-2015 period, the period covered by our Moneyfacts data.

[10]When a bank belongs to a multiple-banks group, we keep it separate from other banks within the same group when measuring its Google search volume and computing bank-time fixed effect. This is a more conservative approach because, unlike different brands within a bank, different banks within a group have separate balance sheets and prudential requirements. Therefore, deposits raised by different banks within a group might not be fully fungible, and the risk faced by a depositor might not be exactly the same. This makes a difference for two groups: Lloyds Banking Group and RBS Group.

2 Google Searches and Depositors' Risk Perceptions

In this section, we explain our measure of *Abnormal Searches* and of public signals about banks. We then explore the relationship between *Abnormal Searches*, deposit flows, and public signals.

2.1 *Abnormal Searches*

For illustration, Figure 1 plots the behavior of the raw Google search volume for the term "Northern Rock" during the 2007 run for Northern Rock. On August 9th, interbank money markets froze and four days later Northern Rock informed the UK Financial Services Authority that it had lost access to wholesale funding markets, on which it relied heavily. However, this information was not disclosed publicly. Consistent with this, the search volume remains broadly flat during that week, despite the run by wholesale depositors depleting the bank's entire liquid asset buffer during this period (Shin, 2009). A month later, on September 14th, the Bank of England publicly announced the provision of emergency liquidity assistance to Northern Rock, triggering a widely publicized run by retail deposits at the bank's branches. As Figure 1 illustrates, search volume peak on that week.

In order to illustrate the behaviour Google data over a longer time period, Figure 2 plots the monthly UK search volume for "deposit insurance" during the financial crisis period. Expectedly, the time series reaches its peak in October 2008, when the UK government announced the public recapitalisation of two of the largest UK banks (Lloyds and RBS). The search volume also surges during the run on Northern Rock, and when Halifax-Bank of Scotland share prices collapsed amidst rumors of imminent failure.

More generally, one challenge is that Google search volumes might also fluctuate with searches unrelated to depositors' risk perceptions, such as searches for branch-opening times or for the bank's website. Unlike those reflecting depositor worries, however, it is not immediately obvious why such searches should fluctuate substantially during concentrated periods of time. Following Da et al. (2011), we thus transform the raw Google Trends data into a measure of abnormal search volume for a given bank, defined as:

$$Abnormal\,Searches_{b,t} = log(Volume_{b,t}) - log(Median\,[Volume_{b,t-1}, ..., Volume_{b,t-8}]) \quad (1)$$

where $Volume_{b,t}$ is the search query share for the name of bank (or brand for multiple-brand banks) b during week t.

2.2 Negative Signals about Banks

In order to test whether *Abnormal Searches* respond to negative public signals about banks, we create two variables. Our first variable proxies for negative signals from financial markets using CDS prices available for a subset of the largest UK banks. Our second variable proxies for negative signals in the media by transforming our UK newspaper articles database in two ways. First, we follow the literature and create a measure of the negative sentiment conveyed by each article using the dictionary of words with positive and negative connotation developed by Loughran and McDonald (2011). Second, we aggregat this measure by bank/brand and week, and we compute the following index:

$$NegativeCoverage_{b,t} = \sum_{a}^{A} \frac{\#Negative\,Words_{a,b,t} - \#Positive\,Words_{a,b,t}}{\#Words_{a,b,t}} \quad (2)$$

where a indexes all article mentioning bank/brand b during week t. The more articles, and the more negative these articles are, the higher the *Negative Coverage* index. Following our treatment of the search volume data, we then compute an *Abnormal Negative Coverage* measure that subtracts *Negative Coverage* at time t from its median value over the past eight weeks.

2.3 Abnormal Searches and Deposit Flows

In order to assess whether *Abnormal Searches* is a good proxy for depositors' perception of risk, we first explore its relationship with deposit balances at UK banks. Unlike the Deposit Rates Dataset, our Deposit Balances Dataset covers a subset of all UK banks at monthly frequency and does not distinguish between brands and jurisdictions (Section 1.2 for details). However, a key advantage that this data is broken down by depositor type. This allows us to study the relationship between *Abnormal Searches* and the behavior of three different types of depositors: individuals; public non-financial firms; and financial firms. We provide summary statistics for deposit balances across all depositor groups in Table 3.

For each of these groups, we separately estimate the following simple model:

$$\Delta Deposit\,Balance_{i,t} = \alpha + \beta \cdot Abnormal\,Searches_{i,t} + \epsilon_{i,t} \tag{3}$$

where $\Delta Deposit\,Balance_{i,t}$ is the first difference of the logarithm of total balances held by a given depositor group in bank i at the end of month t. $Abnormal\,Searches_{i,t}$ is the abnormal search volume for a bank and month. Since our original Google data is weekly, we average it by bank/brand and month before computing *Abnormal Searches* using equation 1. When a bank has multiple brands, we use search data for this bank's main brand – for instance "HSBC" for HSBC Bank (see column 1 of Table 2 for a list of all the main brands).

The results reported in Table 4 highlight two key findings. First, increases in *Abnormal Searches* are associated with decreases in deposit balances. This is consistent with the idea that surges in information collection are associated with declining risk perceptions and an increased probability of withdrawals (He and Manela, 2016). This finding also suggests that *Abnormal Searches* is not mainly driven by neutral searches (e.g. for branch-opening times) or positive ones (e.g. searches for higher-yielding deposit products), in which case the relationship between

Abnormal Searches and deposit balances should have been insignificant or positive.

Second, the relationship between *Abnormal Searches* and deposit balances is only statistically significant for balances held by individuals (column 1), but not with those held by other depositors (column 2). Within the second group, the relationship is insignificant for both private non-financial firms (column 3) and financial firms (column 4). While we don't have detailed information about depositors within these groups, these results are consistent with the idea that Google searches primarily reflect information collection by the general public, as opposed agents with potential access to other sources of information. This interpretation coincides with prior evidence that Google search volumes for US stock tickers capture the demand for information by retail investors (Da et al., 2011), and that this demand is only weakly correlated with that of institutional investors with access to proprietary information (Ben-Rephael et al., 2017).

From an economic standpoint, the relationship between *Abnormal Searches* and individuals' deposit balances is relatively small: a one-standard deviation increase in *Abnormal Searches* (+23 percentage point) is associated with a 0.3 percentage-point outflow. However, this effect could mask a larger underlying change in the risk of withdrawals (He and Manela, 2016), as well as a parallel increase in deposit rates by banks aimed at mitigating this risk (Egan et al., 2017). Quantifying this mechanism is the objective of our main test in the Section 3. One key challenge in that context is to identify whether banks respond to declining depositors perception and the associated risk of withdrawal over and above their potential response to realized withdrawals and the fundamentals that might prompt them. To address this issue we exploit the fact that, unlike the Deposit Balances Dataset used in this section, our Deposit Rates Dataset distinguishes between rates offered by different brands of a same bank. This allows us to exploit variation in *Abnormal Searches* within banks and time periods, thus controlling for time-varying bank-level fundamentals, including outflows.

2.4 Negative Signals and Abnormal Searches

The finding that *Abnormal Searches* is correlated with withdrawal decisions by individuals is consistent with the notion that abnormal information-gathering coincides with instances of declining risk perceptions about banks (He and Manela, 2016). In this section, we test the idea that changes in these perceptions are associated with the arrival of negative signals about a bank (Goldstein and Pauzner, 2005).

We consider two potential sources of public signals about banks' risk: CDS prices and our *Abnormal Negative Coverage* index of newspaper articles about banks. We start by exploring contemporaneous correlations between these variables and *Abnormal Searches*; we do so using weekly data for twelve UK banks indicated with a † superscript in Table 2 for which CDS data is available. Panel A in Table 5 shows that *Abnormal Searches* is positively correlated with both *Abnormal Negative Coverage* and *CDS Prices*. Periods of heightened information acquisition about a bank thus coincide with times in which UK newspapers report more negative news about this bank, and in which financial market participants demand higher credit risk premia against this bank. In turn, *Abnormal Negative Coverage* is also positively correlated with *CDS prices*, suggesting that negative financial market developments feed into negative newspaper coverage, or vice versa. However, these correlations never exceed 0.18, suggesting that these three variables have related but distinct dynamics.

To better understand the dynamic relationships between these variables, we follow Da et al. (2011) and estimate a panel vector autoregressive (PVAR) model. We include four lags of each variable and impose no restrictions on their relationship to estimate the coefficients. In addition, we apply the standard Helmert transformation to eliminate any time-invariant effects. In Panel B of Table 5, we report parameter estimates for the first lag of each variable for brevity. *Abnormal Searches* respond positively to one-week lags of *Abnormal Negative Coverage* and *CDS*

Prices. By contrast, *Abnormal Negative Coverage* and *CDS Prices* do not respond to lagged *Abnormal Searches*. Moreover, *CDS prices* do not respond to *Abnormal Negative Coverage*. These results are consistent with the idea that depositors tend to lag behind presumably better informed agents (Schliephake and Shapiro, 2018) and with evidence that institutional stock market investors' attention leads retail investors' (Ben-Rephael et al., 2017)

Albeit suggestive only, the results in this section support the use of *Abnormal Searches* as a proxy for depositors' risk perceptions. However, the evidence also suggests that changes in depositors' perceptions are correlated with changes in signals from financial markets and media, and that these signals might be correlated with unobserved fundamental factors.[11] In the next section we describe our empirical strategy to address these issues and isolate banks' response to depositors' risk perceptions from the potential response to confounding fundamentals.

3 Banks' Response to Depositors' Perceptions

In this section we investigate how banks respond to changes in depositors' risk perceptions. We first describe our identification strategy and baseline results. We then study how banks' response varies cross-sectionally and perform a series of robustness tests.

3.1 Identification Strategy: Banks and Brands

The key challenge in identifying banks' response to declining depositors' perceptions is that changes in *Abnormal Searches* are correlated with public signals about banks, deposit outflows, and potentially with changes in underlying fundamentals unobservable to the econometrician (Section 2). Therefore, a naïve estimate of the relationship between deposit rates an *Abnormal*

[11] For instance, when their CDS premia rise, banks might struggle to raise wholesale funding and equity, hence generating larger demand for retail deposits (Billett and Garfinkel, 2004). Studies that use Google data to measure stock-market investors' sentiment have addressed concerns about correlations between perceptions and fundamentals by using high-frequency market-based controls (Da et al., 2014); such proxies are unavailable for most banks in our sample and are necessarily imperfect in the case of banks given the potential distortion of banks market prices associated with implicit public guarantees. We thus base our approach on fixed effects instead.

Searches might reflect banks' response to these factors rather than to depositors' perceptions.

To address this issue, we exploit the fact that many UK banks offer the same deposit products under different brands.[12] Brands are not legally separate entities within a bank from a regulatory and accounting standpoint. As a consequence, brands are are irrelevant for the risk faced by the depositor. In line with this idea, brands do not have separate deposit-taking licences, and licensed banks must aggregate deposit balances across all their brands for the purpose of deposit insurance coverage calculations. By the same token, brands are irrelevant for the value of a deposit to the bank. Since brands do not have separate balance sheets within banks, deposits are fully fungible within banks regardless of their brands - that is, all deposits serve the same set of outstanding assets and investment opportunities

However, brands can appear as distinct entities in the eyes of depositors because of the dedicated branding, marketing, and customer service strategies that banks use in order to differentiate brands.[13] This means that depositors tend to be primarily familiar with brand names, and not necessarily with the brand's parent entity. This discrepancy implies that depositors (or a subset thereof) with different brands of the same bank can have different perceptions of the risk they face, in particular during periods of heightened uncertainty about banks. Post-crisis regulatory attempts to reduce the "customer confusion" created by multi-brand bank architectures support this notion (Treasury Select Committee, 2009). In particular, banks were forced to disclose their entire brand portfolio in communications with prospective depositors from

[12]Banks typically choose to operate under multiple brands for two main reasons. First, after a merger, the acquirer often opts to maintain the acquired bank's brand, for instance owing to the costs of harmonizing marketing and branch networks. For example Nationwide maintained the Dunfermline, Derbyshire and Cheshire Building Society brands after acquiring them in 2008-2009. At this point however these banks stopped existing as standalone institutions, instead becoming mere divisions of Nationwide. Second, banks might create separate brands in order to target specific clienteles; for instance HSBC's First Direct differentiates itself from HSBC because its customer service operates per telephone and internet only. Our baseline regression controls for unobserved heterogeneities across brands (with brand fixed effects) and depositor types (with deposit product-week fixed effects). The latter set of fixed effects control for whether a deposit has a telephone or internet-only customer service.

[13]Consistent with this, industry rankings of customer service and reputation are typically done at the brand level. The potential disconnect between the perceptions of different brands in the eyes of company owners and consumers associated with multi-brand strategies is well documented in the marketing literature. See for instance Åsberg (2015) and references therein.

2011 onwards. This was to mitigate the risk that depositors would underestimate the share of their deposit in excess of deposit insurance if they split their deposits across different brands of the same bank, even though deposit balances are consolidated by bank for deposit insurance coverage calculations.

3.2 Empirical Model

Since depositors' risk perceptions can vary across the brands of a same bank whereas the actual risk to depositors cannot, we can estimate the relationship between deposit rates and shifts in *Abnormal Searches* while controlling the underlying risk and any other fundamental determinant of deposit rates via bank-time fixed effects. More specifically, we use the following model:

$$Deposit\,Rate_{b,p,t} = \beta \cdot Abnormal\,Searches_{b,t-1} + \phi_{i,t} + \gamma_{p,t} + \eta_b + \epsilon_{b,p,t}, \quad (4)$$

where $Deposit\,Rate_{b,p,t}$ is the rate offered by bank (or brand for multiple-brand banks) b for deposit product p in week t, and *Abnormal Searches* is the abnormal Google search volume for the name of brand/bank b in the preceding week.

Our main hypothesis suggests that β should be positive – that is, banks should respond to declining risk perceptions and the associated risk of withdrawals by offering relatively higher deposit rates. The bank-week fixed effects ($\phi_{b,t}$) allow us to test this idea while controlling for all time-varying aggregate or bank-level fundamental factors that potentially determine deposit rates, including those hard to measure such as the bank's investment opportunities (Ben-David et al., 2017).

Our model includes additional fixed effects in order to address other potential confounding factors. First, product-week fixed effects ($\gamma_{p,t}$) capture shifts in the demand for different deposit types common to all banks/brands in a given time period. Second, brand fixed effects

(η_b) control for time-invariant differences across brands, such as access to branches, customer service quality, or clientele type. Finally, in our most conservative specification, we additionally include bank-product-week fixed effects in order to control for the fact that brands might offer differentiated products in order to cater to different clienteles.

We address a potential reverse causality problem whereby changes in rates could cause surges in *Abnormal Searches* further below. To do so we consider different lags of *Abnormal Searches*, and we show that its relationship with deposit rates varies cross-sectionally in a way that does not appear consistent with a reverse causality mechanism.

3.3 Baseline Results

We report the results of different variants of our baseline model in Table 7.[14] In column 1 we only include our main regressor of interest *Abnormal Searches*. We then add further bank-level controls (column 2) and different sets of fixed effects (columns 3-6). The parameter estimate for *Abnormal Searches* is positive and statistically significant in all columns. That is, the more abnormal demand for information about a bank/brand, the higher this bank/brand's deposit rates the following week. These results are consistent with the idea that abnormal information acquisition coincides with deteriorating depositors perception of risk (He and Manela, 2016), and that banks react to the associated increase in the risk of withdrawal by offering higher deposit rates (Egan et al., 2017).

This result remains significant to the 1% confidence level when we only exploit variation across brands of the same bank by including bank-week fixed effects (columns 4-6). This suggests that a significant part of banks' response cannot be explained by confounding changes in observable or unobservable dimension of the bank's riskiness, or any other fundamental deter-

[14] We provide summary statistics for the variables used in these regression in Table 6. Standard errors are clustered by bank. Below we report baseline results where standard errors are clustered by banking group and week instead.

minant of deposit rates such as investment opportunities. Instead, the residual part of banks' response must be explained by a brand-specific response to a brand-specific change in *Abnormal Searches*. This is also true when we additionally include bank-product-week fixed effects (column 6), thus focusing on variation in deposit rates across brands for the same deposit product. This result suggests that the possibility that different brands might cater to different clienteles by offering dedicated different deposit products does not affect our key result.

Economic Magnitude Our estimates suggest an economically significant relationship between depositors' perceptions, banks' earnings, and the costs of withdrawal to depositors. Specifically, column 1 estimates suggest that a two standard-deviation increase in *Abnormal Searches* – a shock experienced by most large UK banks in the week during which Lehman Bros. filed for bankruptcy – is associated with a 16 basis point increase on a £10,000-minimum deposit. This increase represents around 20% of the average 2008 net interest margin for UK retail-focused banks. This "premium" also largely exceeds the interest-rate loss that a depositor would face by decreasing her balance from £100,000 to £10,000 (7 basis points on average). Finally the premium is around a third of the opportunity costs for depositors of not switching to another bank, as crudely proxied by the average standard deviation in deposit rates across banks for a given deposit product category and time period (56 points).

Since they do not control for confounding fundamentals, the estimates in column 1 probably over-estimate banks' response to depositors' perceptions. In contrast, the results in columns 4-6 mechanically under-estimate this response, since these regressions only exploit variation in perceptions across brands of a same bank, hence discarding the presumably more substantial variation in risk perceptions *across banks*. Consistent with this idea, the effect of *Abnormal Searches* decreases by a factor of seven in these specifications, relative to column 1. These results might also under-estimate banks' response to depositors' risk perceptions because they are driven by multiple-brand banks only, which are typically larger and hence potentially deemed too-big-to-fail by some depositors. Finally, we obtain significantly larger estimates of banks' response to *Abnormal Searches* when we distinguish between different periods or deposit types (Sections 3.4 and 4).

Robustness In Table 8, we probe the robustness of our baseline model. First, we drop banks receiving a public capital injection during the crisis, since deposit rates could be less informative of fundamentals for these banks (Ben-David et al., 2017); we find similar results (column 1). Next, we test whether our results are driven *only* by unusually large values of *Abnormal Searches*. To do so we drop observations where *Abnormal Searches* is more than two standard deviations away from the mean, finding similar results (column 2). Finally, we cluster standard errors by banking group (column 3) and week (column 4) and find smaller standard errors in both cases.

3.4 Variation across Time and Deposits

We then explore how our key result varies in the time-series and cross-sectional dimensions. Our objective is to test whether our result varies in a way that is consistent with our preferred interpretation, and not with alternative hypotheses including a reverse-causality mechanism.

Our preferred interpretation of our key result is that when depositors' perceptions deteriorate banks offer higher deposit rates in order to make withdrawals more costly. In turn, this idea suggests that the link between deposit rates and *Abnormal Searches* should be stronger for deposit products that permit early withdrawals. In Table 9, we thus separate deposit products that do not require a withdrawal notice (typically current accounts) from other deposit types with withdrawal restrictions. We find that the positive relationship between deposit rates and *Abnormal Searches* only holds for deposits without withdrawal notice requirements (column 1) and not for other deposits (column 2). This is consistent with the idea that our main results reflects a motive by banks to mitigate increased perceptions of risk and the associated risk of early withdrawals by existing depositors. In contrast this result seem inconsistent with a reverse-causality mechanism, since it is unclear why an increases in deposit rates would only attract more online searches in the case of instant-access deposits.

Next, we explore different deposits sizes. Our baseline specification uses the rate on £10,000-minimum deposits since this is the category for which we have the most data points. In Table 10 we instead use observations for all minimum-deposit amounts between £1,000 and £150,000 in the same panel, estimating a separate *Abnormal Searches* coefficient for each deposit-size group. The results show that increased abnormal searches are associated with higher deposit rates for all deposit sizes but the smallest one. Moreover, the response increases with deposit size: the estimate for a £5,000 deposit is 0.034, against 0.075 for a £150,000 deposit. Whether this stronger response is due to deposit size, depositor sophistication, or deposit insurance coverage is unclear. We return to the issue of deposit insurance in a setting that allows us to separate these factors in Section 4.[15]

Following Artavanis et al. (2019), we then separate normal times from periods of aggregate uncertainty about the banking system, during which depositors are more likely to worry about the safety of their deposits. Specifically, we run a separate regression for the financial crisis period (September 2007 to November 2009) and for the remainder of our sample period. The results reported in Table 11 show that our key finding is driven by the crisis period. More specifically, the coefficient for the crisis period is large in magnitude and statistically significant

[15] The fact that we find a significant effect for deposits clearly below the UK deposit insurance coverage threshold is consistent with two known frictions in the scheme. First, like in India (Iyer and Puri, 2012), UK deposit insurance claims were intentionally paid out with a long delay: in February 2007 for instance the FSCS website said that "after a firm has been declared in default, FSCS generally aims to process your claim within six months of receiving your application form". This is noteworthy since immediate liquidity needs are a quantitatively important motive for insured depositors to withdraw (Artavanis et al., 2019). Second, UK authorities found that public awareness of UK deposit insurance was low during the crisis and its aftermath, and that this could have contributed to "increasing the likelihood of a run on a deposit taker, as was seen with Northern Rock in 2007" (Financial Conduct Authority, 2009).

at the 5% level, whereas it is smaller and statistically indistinguishable from zero in normal times.

Last we consider different lags of *Abnormal Searches*. If banks increase deposit rates to retain depositors who perceive increased risk as our key hypothesis suggests, we would expect this effect to persist for some time. In contrast, if our results reflect a reverse-causality mechanism in which changes in deposit rates lead to increased search volumes, further lags should be insignificant. To test this idea, we repeat the baseline regression for different lags of *Abnormal Searches*, and report the results in Table 12. The significant relationship between deposit rates and *Abnormal Searches* persists for at least two months, although the coefficient size expectedly weakens somewhat with higher lags.

3.5 Controlling for Newspaper Coverage

In Section 2 we have shown that *Abnormal Searches* increase with negative newspaper coverage about UK banks. One interesting question is whether deposit rates respond to changes in *Abnormal Searches* over and above their possible response to the negative newspaper coverage that might prompt them. This would be consistent with the evidence that published news do not necessarily affect stock prices before they are actually read (Huberman and Regev, 2001).

In Table 13 we test this idea by using our *Abnormal Negative Coverage* index (see Section 2). In Panel A we start by controlling only for *Abnormal Negative Coverage*. As expected, the results suggest that an increase in the supply of news with negative connotation about a bank/brand is associated with this bank/brand offering higher deposit rates on average. In Panel B, we control for both *Abnormal Negative Coverage* and *Abnormal Searches*. We find that only the coefficient for *Abnormal Searches* is statistically significant. This coefficient is around 50% larger than in our baseline regression where *Abnormal Negative Coverage* is not controlled for. While a direct comparison is difficult given the different sample size, this suggests that if anything, not controlling for newspaper coverage implies that our estimate for banks' response to *Abnormal Searches* is biased downwards.

4 The Role of Deposit Insurance

In Section 3 we have established that banks offer higher deposit rates when faced with increased abnormal online search volumes. Our preferred interpretation of this result is that banks respond to declining depositors' risk perceptions by making withdrawals more costly to depositors (Egan et al., 2017). We have also found that this effect increases in strength with deposit size, consistent with the idea that banks must respond more strongly to depositors with balances in larger excess of the UK deposit insurance limit (Section 3.4).

In this section, we take a closer look at the role of deposit insurance in a setting that allows a cleaner identification. More specifically we first test the idea that banks' response to declining risk perceptions should be stronger when deposits are uninsured (hence exposing depositors to a larger loss-given-default). Second, we test whether this effect is stronger for banks subject to a higher funding liquidity risk (hence exposing depositors to a larger probability of default). To do so we exploit the fact that most large UK banks offer similar deposit products in the UK and the British Crown Dependencies, and that deposit insurance differs across these jurisdictions.

4.1 Institutional setting

Albeit formally owned by the British Crown, the Bailiwicks of Jersey and Guernsey and the Isle of Man (jointly known as The Crown Dependencies) are self-governing territories and are not members of the UK or European Union (Figure 3). They have independent legislative and executive powers and authorities, including for banking supervision. Still, the Dependencies' legal systems are based on English common law, their currencies are pegged to the British Pound, and their inhabitants are British citizens.

This peculiar relationship is also reflected in closely intertwined banking systems. In particular, a majority of UK banks in our dataset – those tagged with a * superscript in Table 2 – offer deposits in the UK ("onshore") and in the Crown Dependencies ("offshore"). UK banks sometimes offered these deposits through a branch or subsidiary in the Dependencies. Even in these cases, however, banks typically use their UK brand to market these deposits, sometimes with an additional suffix. For instance, Alliance & Leicester offers offshore deposits under the Alliance & Leicester Int. brand. In addition, because offshore deposit balances largely exceed local investment opportunities, the bulk of these deposits are typically transferred back to the UK parent's balance sheet.[16] While the Dependencies' GDP are relatively small compared to that of the UK, anecdotal evidence suggests that offshore deposits could provide a substantial source of funding to some UK banks. For instance, offshore deposits represented 18% of total deposits for Northern Rock in December 2006 (Shin, 2009).[17]

Offshore deposits offered by UK banks are routinely advertised alongside onshore deposits in the Moneyfacts magazine and website as well on banks' own website, meaning they are widely accessible to UK retail depositors. The main interest for such depositors to open up an offshore account with a UK bank is not tax-related, as these deposits are subject to standard UK taxes.[18] Instead one important benefit of offshore deposits is their convenience for current or former expatriates. Because of UK anti-terrorism and anti-money-laundering legislations, a prospective depositor must have a UK domicile in order to open a bank account in the UK, whereas this is not necessary for offshore accounts. Still, offshore deposits give access to most of

[16]According to a 2016 survey, £120 of £200 billion held in Jersey banks are up-streamed to UK banks (Capital Economics, 2016).

[17]The majority of banks operating in the Dependencies are UK-based, as is a substantial share of the retail customers served by these banks. For instance, 30 of 47 banks operating in the Isle of Man by March 2007 were UK-based. According to a survey, UK customers represented 42% of Jersey banking funds in 2015-2016 (Capital Economics, 2016).

[18]The only difference is that UK taxes on interest earnings are automatically deducted on onshore accounts, whereas they are perceived once a year on offshore deposits. The offshore deposits described in this paragraph are only accessible to individuals, as opposed to corporates or trusts, which can use different offshore deposit products for a number of other motives.

the services attached to onshore deposits, including payments and cash withdrawals in the UK. Therefore, offshore accounts allow depositors to keep on making payments in Sterling without necessarily being domiciled in the UK.[19]

Despite their overlap, the UK and Crown Dependencies banking systems do not share a common deposit insurance scheme. At the beginning of our sample period (2007), the UK Financial Services Compensation Scheme (FSCS) fully insured the first £2,000 of any onshore deposit with an UK-licensed bank, as well as 90% of the next £33,000. The coverage was extended to 100% of deposits up to £50,000 in October 2008. In contrast, offshore deposits with UK-licensed banks are not covered by the FSCS but by the Crown Dependencies' own deposit insurance. Guernsey introduced its Banking Deposit Compensation scheme in November 2008, covering up to £50,000 per qualifying deposit and bank. Jersey launched a similar Depositors Compensation Scheme in November 2009.

4.2 Identification Strategy

The peculiar relationship between the UK and the Crown Dependencies creates variation in deposit insurance coverage within a same bank/brand and time period. Specifically, a depositor in a given UK bank/brand faces the exact same risk that this bank might default, whether her deposit is onshore or offshore. In contrast a depositor in a Dependency that does not offer deposit insurance would contemplate a higher loss-given-default. We conjecture that, as a result, the bank would need to offer this depositor a relatively higher compensation in order to mitigate the risk of withdrawals associated with declining risk perceptions. We further conjecture that this effect should be stronger for banks that face a higher probability of default.

To test these two ideas, we use our Onshore/Offshore Database, which adds offshore deposits

[19]Consistent with this, the Guardian Newspaper writes: "Mention offshore accounts and many people think of wealthy expats, tax evaders and millionaire "non-doms". Yet Guardian Money has been in contact with dozens of account holders this week, and most are far removed from that image. Many are UK citizens - development workers, teachers, project managers and the like - who happen to be living abroad". https://www.theguardian.com/money/2008/oct/18/savings-familyfinance.

offered by UK banks to the Deposit Rates Database used in Section 3. We then augment the empirical specification of Section 3 as follows:

$$Deposit\,Rate_{b,p,j,t} = \beta \cdot Uninsured_{j,t} \times Abnormal\,Searches_{b,t-1} + \zeta_j + \kappa_{b,p,t} + \lambda_{o,t} + \sigma_{b,p,j,t} \quad (5)$$

where $Uninsured_{j,t}$ is set to one in jurisdictions and time periods where a £10,000 deposit is not insured, and 0 otherwise. Our first hypothesis suggests that β should be positive – that is, when abnormal searches for a given brand/bank increase, this bank/brand must offer a relatively larger deposit rate for its offshore deposit products, relative to its onshore products. For instance, our prior is that the deposit rate on an offshore HSBC-brand deposit would be more responsive to increased abnormal searches for "HSBC", relative to rates on an otherwise similar onshore HSBC-brand deposit. We test this idea while controlling for time-invariant differences across jurisdictions by including jurisdiction fixed effets (ζ_j). In order to test our second hypothesis, we further interact the main coefficient of interest with a proxy for the bank's funding liquidity risk.

One challenge is that offshore depositors might differ from other depositors for reasons other than deposit-insurance coverage, such as their wealth, sophistication, ability to move funds across accounts, or age. In turn, these factors might bias our results insofar as they can affect banks' response to declining risk perceptions. While these factors might be relatively constant over time (unlike insurance coverage), we mitigate this issue by progressively saturating the model with two additional sets of fixed effects. First, we include brand-product-week fixed effects ($\kappa_{b,p,t}$); this means that we only exploit variation witin relatively more homogenous clienteles seeking the same product type and brand at a given point in time. Second, we include offshore-week fixed effects ($\lambda_{o,t}$) in order to mitigate any residual heterogeneities across onshore and offshore depositors, including those varying over time.

4.3 Results

We report the results of different variants of model 5 in Table 14. In column 1, we only include the *Uninsured* dummy, as well as jurisdiction fixed effects. The results suggest that deposit rates are 119 basis points higher on average in jurisdictions and time periods without deposit insurance.[20]

In column 2, we add *Abnormal Searches* and its interaction with *Uninsured*. Similarly to our baseline results, the positive coefficient estimate for *Abnormal Searches* suggests that banks facing increased abnormal information collection offer relatively higher deposit rates in jurisdictions and time periods with deposit insurance. In turn, consistent with our conjecture, the positive estimate for *Abnormal Searches* $\times$ *Uninsured* suggests that the sensitivity of deposit rates to changes in *Abnormal Searches* is around three times higher in jurisdictions and periods without deposit insurance.

This result suggest that when perceptions decline, depositors not covered by insurance must be offered a relatively larger compensation in order for banks to mitigate the risk of withdrawals. This is consistent with the idea that relative to other depositors in the same bank, uninsured depositors are exposed to a higher loss-given-default.

One natural hypothesis is that differences in loss-given-default within a bank should be exacerbated when this bank's probability of default (or liquidity shortage) is higher. To test this idea, in Column 3 we interact *Abnormal Searches* $\times$ *Uninsured* with *Retail Funding*, defined as the share of a bank's total liabilities in the form of deposits by individuals. We do so following extensive evidence that retail deposits are relatively less run-prone than other forms of bank liabilities (Egan et al., 2017), suggesting that a higher initial share of retail deposits lowers the

[20] Difference in a banks' investment opportunities onshore vs. offshore are unlikely to explain this difference because the bulk of offshore deposits is typically 'up-streamed' to the parent bank, meaning these deposits finance the same set of lending opportunities. This contrasts with the US context, where there can be differences in investment opportunities across the different local branches of a same bank (Ben-David et al., 2017).

risk that bank distress results in default.[21] The results in column 3 of Table 14 are consistent with this idea: the parameter estimate for the interaction of *Abnormal Searches* $\times$ *Uninsured* and *Retail Funding* is negative, suggesting that the effect of deposit insurance on banks' response to abnormal searches is weaker for banks with more retail funding.

In the remaining columns, we increasingly saturate the empirical model with fixed effects in order to control for potential omitted variables. In column 4, we add brand-week fixed effects, thereby only concentrating on variation across insured and uninsured deposits issued by the same brand and in the same time period. The key interaction terms remain statistically significant, suggesting that our results are not driven by unobserved differences across banks or brands that chose to offer offshore deposits or not. Still, one concern is that the same brand might offer different products onshore and offshore given the potential difference in clienteles. In column 5 we therefore add brand-week-product fixed effects. This also leaves our key estimates broadly unchanged. A final concern is that differences in within the same brand, deposit product and time period might reflect heterogeneities in clientele type (e.g. sophistication) rather than deposit insurance. To test this idea we add offshore-time period fixed effects in column 6, in order to control for unobserved differences in onshore and offshore clienteles over time. Our results are again broadly unchanged.

Together, the results in this section reinforce the idea that, although depositors might be informed by noisy signals (Goldstein and Pauzner, 2005), declining risk perceptions have a larger impact on deposits exposed to a higher loss-given-default and probability of default. This suggests that declining depositors' perceptions provide a source of potential discipline for riskier banks and products. This complements evidence that retail depositors are insensitive to

[21] In addition, a given increase in *Abnormal Searches* is more likely to lead to negative search results in the case of banks, such that this increase might be associated with a higher risk of withdrawals. For instance, a depositor searching for "Northern Rock" on Google in September 2007 would have been more likely to find articles describing the bank's business model in a negative light, relative to other UK banks. While our liquidity risk proxy is calculated using confidential data, more sophisticated depositors would also have been able to retrieve similar information from banks' own reports. For instance, the 2006 Northern Rock Annual Report reports a wholesale funding ratio.

bank risk in normal times (Hanson et al., 2015).

5 Conclusion

This paper provides empirical evidence for the theoretically prevalent idea that shifts in depositors' perceptions of risk can be a source of dicipline and potential fragility for banks. We exploit a setting where banks simultaneously offer deposits via multiple brands and in several jurisdictions, allowing us to study the effect of depositors' risk perceptions and the role of deposit insurance in that context while controlling for both observable and unobservable underlying fundamental risk factors.

Using online search volume for the name of a bank as a proxy for depositors' risk perceptions, we find that the abnormal volume of online information acquisition about UK banks increases in response to negative signals about these banks in newspapers and financial markets. In turn, increased abnormal information acquisition towards a bank is associated with this bank offereing higher deposit rates during the 2007-2009 crisis. This is particularly true for deposits that can be withdrawn more easily by depositors. Banks' response to abnormal information acquisition is stronger in the absence of deposit insurance, particularly for banks with greater funding liquidity risk. Importantly, all these results hold when confounding aggregate or bank-specific changes in fundamentals are controlled for using comprehensive sets of fixed effects.

Overall our results point to a perception-driven amplification mechanism, whereby declining risk perceptions about a bank put pressure on this bank to offer higher rates in order to retain depositors, thus eroding its profitability. Quantifying the contribution of risk perceptions to aggregate fragility in a general equilibrium model a la Egan et al. (2017) consistutes an interesting avenue for future research.

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6 Figures

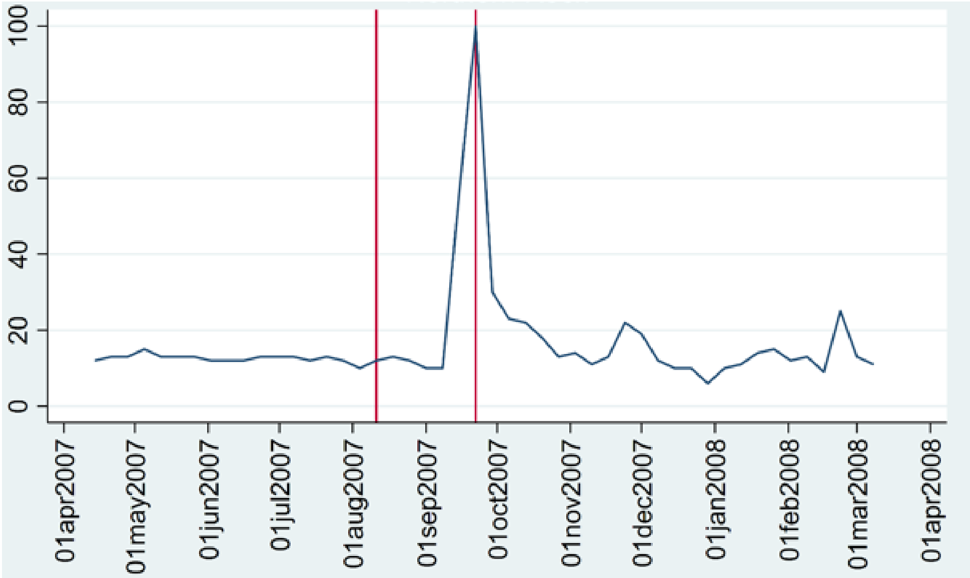

Figure 1: Google UK search volume for "Northern Rock". The first vertical line indicates the day during which Northern Rock privately disclosed to the UK Financial Services Authority that it had lost access to wholesale funding markets. The second vertical line indicates the day during which the Bank of England publicly announced the provision of emergency liquidity assistance to Northern Rock. Data source: Google Trends.

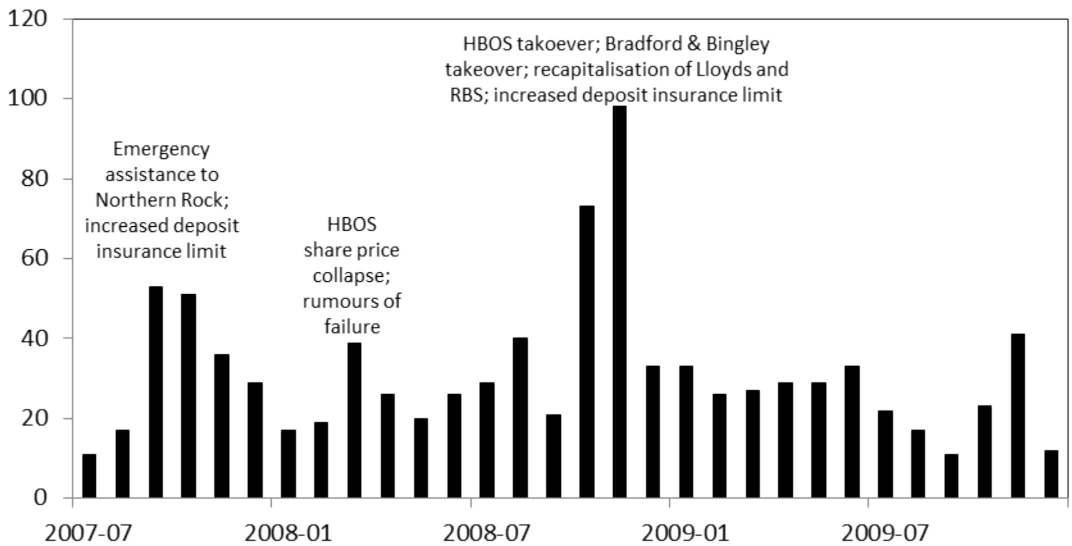

Figure 2: Google UK Search Volume for "Deposit Insurance" by UK individuals. Data source: Google Trends.

Figure 3: Geographical Location of British Crown Dependencies (within dark shades circles): Isle of Man (top), Jersey, and Guernsey (bottom).

7 Tables

Table 1: Variables Definitions and Sources

	(1) Definition	(2) Raw Data Source
Bank Variables		
Capitalisation	Total Capital (% Total Assets)	Bank of England (BT)
Retail Funding	Deposits by UK-Resident Individuals (% Total Assets)	Bank of England (BT)
Real Estate Loans	Loans, Advances and Facilities to UK-resident borrowers in real estate, professional services and support activities (% Loans, Advances and Facilities to UK-resident borrowers)	Bank of England (AL)
Bank Loans	Loans, Advances and Facilities to UK-resident financial intermediaries (% Loans, Advances and Facilities to UK-resident borrowers)	Bank of England (AL)
Provisions	Final level of provisions (% Total Assets)	Bank of England (PL)
Return on Assets	Pre-tax profit on ordinary activities-Provisions-Taxes) (% Total Assets)	Bank of England (PL)
Asset Growth	(Total Assets$_t$-Total Assets$_{t-1}$)/Total Assets$_{t-1}$	
Cash	Cash and UK Treasury Bills (% Total Assets)	Bank of England (BT)
Total Assets	Log Total Assets	Bank of England (BT)
Bank-Brand Variables		
Abnormal Searches	log(Search Frequency$_t$)-log(median(Search Frequency$_{t-1}$,...,Search Frequency$_{t-8}$))	Google Trends
Negative Coverage	Sum of net fraction of negative words in all newspaper articles about bank/brand, minus average sum over past eight weeks.	Factiva

Notes: This table reports the definition (column 1) and data source (column 2) of key variables. Initials in parentheses indicate Bank of England regulatory returns.

Table 2: Banks and Trading Brands (* indicates offshore presence)

(1)	(2)
Bank (Group)	Other Brands
Aldermore	
Alliance & Leicester†	
Bank of Scotland*† (Lloyds Banking Group)	Halifax*; Intelligent Finance; Saga; BM Savings
Barclays Bank*†	Woolwich*
Bradford & Bingley*†	
Chelsea Building Society	
Close Savings	
Coventry Building Society	
Cumberland Building Society	
HSBC*†	First Direct
Kent Reliance	
Leeds Building Society	
Lloyds Bank*† (Lloyds Banking Group)	Lloyds TSB*; Cheltenham & Gloucester
Nationwide Building Society*	Dunfermline Building Society; Derbyshire Building Society; Cheshire Building Society
NatWest*† (RBS Group)	
Newcastle Building Society	
Nottingham Building Society	
Principality Building Society	
Progressive Building Society	
Royal Bank of Scotland*† (RBS Group)	Direct Line
Skipton Building Society*†	
The Co-operative Bank*	Bank smile; Britannia*†
TSB	Yes
Ulster Bank	
West Brom Building Society	
Yorkshire Building Society*†	Barnsley Building Society; Chelsea Building Society; Egg

Notes: This table reports the name of deposit-takers included in our sample. Column 1 reports names of banks; the banking group is reported within parentheses for banks affiliated to a multiple-bank group. Column 2 reports the name of other deposit-taking brands operating under the same regulatory licence. Ownership links are as of the last point at which a bank is included in the sample. Asterisks indicate that the deposit taker also offers offshore deposits in the British Crown Dependencies during the sample period.

Table 3: Share of Total Deposit Balances and Changes in Balances by Depositor Types

	(1)	(2)	(3)	(4)
	% Total Bank Deposit Balances		Δ Monthly Balance	
	Average	Standard Deviation	Average (in %)	Standard Deviation (in %)
All depositors			0.55	6.83
Of which:				
- Individuals	0.51	0.13	0.15	5.49
- Non-Individuals	0.49	0.13	-0.47	6.59
Of which:				
- Financial Firms	0.30	0.16	-0.97	15.84
- Private Non-Financial Firms	0.15	0.03	-0.023	13.22

Notes: This table reports summary statistics for the fraction of a bank's total UK deposit balances held by different depositor types (column 1-2) and the monthly log growth of these balances (columns 3-4). Source: Authors' calculations based on monthly Bank of England (ER) data. The data includes all reporting UK-headquartered banks between 2007 and 2015.

Table 4: Abnormal Searches and Deposit Balances

	(1)	(2)	(3)	(4)
Dependent Variable:		Δ *Deposit Balance*$_{i,t}$		
Depositor Type:	Individuals	Non-Individuals All	Financial Firms	Private Non-Financial Firms
Abnormal Searches$_{i,t}$	-0.01**	0.00	0.04	0.01
	(0.01)	(0.02)	(0.05)	(0.04)
N	880	880	880	880

Notes: This table reports the results of monthly panel OLS regressions. The dependent variable Δ *Deposit Balance*$_{i,t}$ is the log monthly change in deposit balances for a given bank and depositor type. Each column includes only deposits held by a depositor type specified in the top row. *Abnormal Searches*$_{i,t}$ is the monthly maximum log Google weekly search volume minus the median log search volume over the past two months. When a bank has multiple brands, we use Google searches for the bank's primary brand. The sample includes a subset of all UK-headquartered banks that file a Bank of England's ER regulatory return in a given month between 2007 and 2015. Standard errors are clustered by banks. Stars indicate significance at 1 (***), 5 (**) and 10% (*) confidence level, respectively

Table 5: Abnormal Searches, News, and CDS Prices

	(1)	(2)	(3)
Panel A: Contemporaneous Correlations			
	Abnormal Searches$_{i,t}$	News$_{i,t}$	CDS Price$_{i,t}$
Abnormal Searches$_{i,t}$			
Abnormal Negative Coverage$_{i,t}$	0.175		
CDS Price$_{i,t}$	0.021	0.131	
Panel B: Panel Vector Autoregression			
	Regression Coefficient	Standard error	
Dependent Variable: News$_{i,t}$			
Abnormal Negative Coverage$_{i,t-1}$	0.41***	0.09	
Abnormal Searches$_{i,t-1}$	-0.01	0.02	
CDS Price$_{i,t-1}$	-0.001***	0.0002	
Dependent Variable: Abnormal Searches$_{i,t}$			
Abnormal Negative Coverage$_{i,t-1}$	0.15**	0.07	
Abnormal Searches$_{i,t-1}$	0.67***	0.04	
CDS Price$_{i,t-1}$	0.001***	0.00	
Dependent Variable: CDS Price$_{i,t}$			
Abnormal Negative Coverage$_{i,t-1}$	31.27	33.23	
Abnormal Searches$_{i,t-1}$	5.50	14.92	
CDS Price$_{i,t-1}$	0.60**	0.28	

Notes: This table reports contemporaneous cross-correlations (Panel A) and results of Panel Vector Autorgression (Panel B) between three weekly variables. *Abnormal Searches*$_{i,t}$ is the weekly search volume for a given bank name minus the median log search volume over the past two months. *Abnormal Negative Coverage*$_{b,t-1}$ is the net fraction of negative words in newspaper articles about a bank/brand, summed by bank/brand and week, minus the log search volume over the past 8 weeks. When a bank has multiple brands, we use Google searches and newspaper coverage for the bank's primary brand. *CDS Price*$_{i,t}$ is the CDS price for a given bank and week, in basis points. The sample includes a subset of all UK-headquartered commercial banks and building societies between 2007 and 2015 for which all three variables are available. Standard errors are clustered by bank. Stars indicate significance at 1 (***), 5 (**) and 10% (*) confidence level, respectively.

Table 6: Summary Statistics: Deposit Rates Dataset

	(1) Mean	(2) Standard Deviation	(3) Observations
Panel A: Brand-Week Variables			
Abnormal Searches	-0.020	0.228	126,616
News	-0.111	2.169	82,055
Panel B: Bank-Quarter Variables			
Capital	0.087	0.066	126,616
Retail Deposits	0.562	0.271	126,616
Real Estate Loans	0.115	0.104	126,616
Financial Intermediaries Loans	0.182	0.177	126,616
Provisions	0.008	0.109	126,616
Return on Assets	-0.050	0.079	126,616
Quarterly Asset Growth	0.147	0.424	126,616
Cash	0.043	0.036	126,616
Log Total Assets	18.001	1.765	126,616
Panel C: Brand-Deposit Product-Week Variables			
Deposit rate (£1,000 minimum)	1.31	1.36	113,356
Deposit rate (£5,000 minimum)	1.34	1.37	122,961
Deposit rate (£10,000 minimum)	1.36	1.37	126,616
Deposit rate (£25,000 minimum)	1.41	1.39	121,253
Deposit rate (£50,000 minimum)	1.41	1.37	114,362
Deposit rate (£100,000 minimum)	1.42	1.37	112,219
Deposit rate (£125,000 minimum)	1.42	1.37	109,972
Deposit rate (£150,000 minimum)	1.43	1.37	109,972

Notes: This table reports summary statistics for key variables of the Deposit Rates Dataset. Variable definitions are reported in Table 1. The dataset includes all onshore Sterling adjustable-rate deposit products offered by all UK-headquartered banks between 2007 and 2015 except building societies with less than 15 branches.

Table 7: Deposit Rates and Abnormal Searches: Baseline Results

	(1)	(2)	(3)	(4)	(5)	(6)
			Dependent Variable: *Deposit Rate*$_{b,d,t}$			
Abnormal Searches$_{b,t-1}$	0.34**	0.35**	0.13***	0.05***	0.05***	0.04***
	(0.14)	(0.14)	(0.04)	(0.02)	(0.01)	(0.01)
Capital$_{i,t-1}$		-1.67	6.353**			
		(1.95)	(2.47)			
Retail Funding$_{i,t-1}$		-2.82***	4.19***			
		(0.83)	(1.13)			
Real Estate Loans$_{i,t-1}$		0.82	-3.40**			
		(0.78)	(1.48)			
Financial Int. Loans$_{i,t-1}$		0.35	2.17**			
		(0.86)	(0.96)			
Provisions$_{i,t-1}$		-0.06	-0.38*			
		(0.07)	(0.16)			
Return on Assets$_{i,t-1}$		0.20	0.06			
		(0.17)	(0.07)			
Asset Growth$_{i,t-1}$		0.49	0.45			
		(0.46)	(0.28)			
Cash$_{i,t-1}$		-6.37*	-0.33			
		(3.30)	(1.52)			
Log Total Assets$_{i,t-1}$		-0.22***	-2.00***			
		(0.07)	(0.49)			
Observations	126,708	126,708	126,708	126,708	119,432	94,901
R^2	0.0033	0.14	0.41	0.60	0.76	0.81
Brand FE			Yes	Yes	Yes	Yes
Bank-Week FE				Yes	Yes	
Product-Week FE					Yes	
Bank-Product-Week FE						Yes

Notes: This table reports the results of OLS panel regressions. The dependent variable *Deposit Rate*$_{b,d,t}$ is the rate offered by deposit brand b for deposit d with minimum deposit amount of £10,000 during week t, in percentage points. *Abnormal Searches*$_{b,t-1}$ is the log Google search volume for brand name b, minus the log search volume over the past 8 weeks. Other controls are defined in Table 1. The sample includes all Sterling adjustable-rate onshore deposit products offered by all UK-headquartered commercial banks and building societies from 2007q1 to 2015q1, except building societies with less than 15 branches. Standard errors are clustered by bank. Stars indicate significance at 1 (***), 5 (**) and 10% (*) confidence level, respectively.

Table 8: Deposit Rates and Abnormal Searches: Robustness Checks

	(1)	(2)	(3)	(4)	(5)
	Dependent Variable: *Deposit Rate*$_{b,d,t}$				
	Drop Bailed Out Banks	Drop FLS Years	Drop Outliers	Group Clustering	Week Clustering
Abnormal Searches$_{b,t-1}$	0.043***	0.076***	0.0491**	0.0496***	0.0496***
	(0.010)	(0.020)	(0.0216)	(0.0107)	(0.0165)
Observations	92,610	81,199	112,612	119,432	119,432
R^2	0.706	0.757	0.767	0.763	0.763
Brand FE	Yes	Yes	Yes	Yes	Yes
Bank-Week FE	Yes	Yes	Yes	Yes	Yes
Product-Week FE	Yes	Yes	Yes	Yes	Yes

Notes: This table reports the results of OLS panel regressions. The dependent variable *Deposit Rate*$_{b,d,t}$ is the rate offered by deposit brand b for deposit d with minimum deposit amount of £10,000 during week t, in percentage points. *Abnormal Searches*$_{b,t-1}$ is the log Google search volume for brand name b, minus the log search volume over the past 8 weeks. Unless otherwise specified, the sample includes all Sterling adjustable-rate onshore deposit products offered by all UK-headquartered commercial banks and building societies from 2007q1 to 2015q1, except building societies with less than 15 branches. Column 1 excludes banks affiliated to a group receiving a capital injection by the UK government in 2008. Column 2 excludes observations from January 2012 onwards, when the Bank of England's Funding for Lending Scheme (FLS) is introduced. Column 3 drops observations for which *Abnormal Searches*$_{b-t-1}$ is more than two standard deviations below or above the sample mean. In column 4 standard errors are clustered by banking group. In column 5 standard errors are clustered by week. Standard errors are clustered by bank in columns 1-3. Stars indicate significance at 1 (***), 5 (**) and 10% (*) confidence level, respectively.

Table 9: Deposit Rates and Abnormal Searches: Different Deposit Products

	(1)	(2)
	Dependent Variable: *Deposit Rate*$_{b,d,t}$	
Included Deposits:	No Witdrawal Notice	Witdrawal Notice
Abnormal Searches$_{b,t-1}$	0.059***	0.019
	(0.017)	(0.023)
Observations	70,644	48,618
R^2	0.728	0.847
Brand FE	Yes	Yes
Bank-Week FE	Yes	Yes
Product-Week FE	Yes	Yes

Notes: This table reports the results of an OLS panel regression. The dependent variable *Deposit Rate*$_{b,d,t}$ is the rate offered by deposit brand b for deposit product d with minimum deposit amount of £10,000 during week t, in percentage points. *Abnormal Searches*$_{b,t-1}$ is the log Google search volume for brand name b, minus the log search volume over the past 8 weeks. The sample includes all Sterling adjustable-rate onshore deposit products without (Column 1) and with a wihdrawal notice (Colum 2) offered by all UK-headquartered commercial banks and building societies from 2007q1 to 2015q1, except building societies with less than 15 branches. Standard errors are clustered by bank. Stars indicate significance at 1 (***), 5 (**) and 10% (*) confidence level, respectively.

Table 10: Deposit Rates and Abnormal Searches: Stacked Panel Regression for Different Deposit Sizes

	(1)
Dependent Variable:	*Deposit Rate*$_{b,d,s,t}$
Abnormal Searches$_{b,t-1}\times$ I(£1,000-minimum Deposit)$_{d,s}$	0.026
	(0.018)
Abnormal Searches$_{b,t-1}\times$ I(£5,000-minimum Deposit)$_{d,s}$	0.034**
	(0.016)
Abnormal Searches$_{b,t-1}\times$ I(£10,000-minimum Deposit)$_{d,s}$	0.042***
	(0.013)
Abnormal Searches$_{b,t-1}\times$ I(£25,000-minimum Deposit)$_{d,s}$	0.032**
	(0.014)
Abnormal Searches$_{b,t-1}\times$ I(£50,000-minimum Deposit)$_{d,s}$	0.044***
	(0.013)
Abnormal Searches$_{b,t-1}\times$ I(£100,000-minimum Deposit)$_{d,s}$	0.077***
	(0.019)
Abnormal Searches$_{b,t-1}\times$ I(£125,000-minimum Deposit)$_{d,s}$	0.074***
	(0.019)
Abnormal Searches$_{b,t-1}\times$ I(£150,000-minimum Deposit)$_{d,s}$	0.075***
	(0.019)
Observations	878,660
R^2	0.760
Brand FE	Yes
Bank-Week FE	Yes
Minimum Deposit Size-Product-Week FE	Yes

Notes: This table reports the results of an OLS panel regression. The dependent variable *Deposit Rate*$_{b,d,s,t}$ is the rate offered by deposit brand b for deposit product d with minimum size s during week t, in percentage points. *Abnormal Searches*$_{b,t-1}$ is the log Google search volume for brand name b, minus the log search volume over the past 8 weeks. *I(x-minimum Deposit)*$_d$ is equal to 1 if deposit product d, s has a minimum deposit size of £x, and 0 otherwise. The sample includes all Sterling adjustable-rate onshore deposit products offered by all UK-headquartered commercial banks and building societies from 2007q1 to 2015q1, except building societies with less than 15 branches. Standard errors are clustered by bank. Stars indicate significance at 1 (***), 5 (**) and 10% (*) confidence level, respectively.

Table 11: DEPOSIT RATES AND ABNORMAL SEARCHES: CRISIS VS. OTHER PERIODS

	(1)	(2)
Dependent Variable: *Deposit Rate*$_{b,d,t}$		
Sample window:	Sep 2007 - Nov 2009	Nov 2009 - Dec 2014
Abnormal Searches$_{b,t-1}$	0.058**	0.012
	(0.028)	(0.017)
Observations	27,791	88,518
R^2	0.84	0.56
Brand FE	Yes	Yes
Bank-Week FE	Yes	Yes
Product-Week FE	Yes	Yes

Notes: This table reports the results of OLS panel regressions for different time periods defined in the top row. The dependent variable *Deposit Rate*$_{b,d,t}$ is the rate offered by deposit brand b for deposit d with minimum deposit amount of £10,000 during week t, in percentage points. *Abnormal Searches*$_{b,t-1}$ is the log Google search volume for brand name b, minus the log search volume over the past 8 weeks. The sample includes all Sterling adjustable-rate onshore deposit products offered by all UK-headquartered commercial banks and building societies from except building societies with less than 15 branches. Standard errors are clustered by bank in columns 1-3. Stars indicate significance at 1 (***), 5 (**) and 10% (*) confidence level, respectively.

Table 12: DEPOSIT RATES AND ABNORMAL SEARCHES: DIFFERENT LAGS

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent Variable: *Deposit Rate*$_{b,d,t}$					
Lag (in weeks):	2	3	4	8	12	52
Abnormal Searches$_{b,t-Lag}$	0.049**	0.048**	0.051***	0.033**	0.016	0.011
	(0.018)	(0.019)	(0.017)	(0.015)	(0.021)	(0.024)
Observations	117,967	117,250	116,518	113,653	110,900	94,172
R^2	0.762	0.761	0.761	0.759	0.757	0.699
Brand FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank-Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Product-Week FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports the results of OLS panel regressions. The dependent variable *Deposit Rate*$_{b,d,t}$ is the rate offered by deposit brand b for deposit d with minimum deposit amount of £10,000 during week t, in percentage points. *Abnormal Searches*$_{b,t-Lag}$ is the log Google search volume for brand name b, minus the log search volume over the past 8 weeks. Lag is the number of weeks, indicated in the top row of the table. The sample includes all Sterling adjustable-rate onshore deposit products offered by all UK-headquartered commercial banks and building societies from 2007q1 to 2015q1, except building societies with less than 15 branches. Standard errors are clustered by bank. Stars indicate significance at 1 (***), 5 (**) and 10% (*) confidence level, respectively.

Table 13: DEPOSIT RATES AND ABNORMAL SEARCHES: CONTROLLING FOR NEWS

	(1)
	Dependent Variable: *Deposit Rate*$_{b,d,t}$
Panel A	
Abnormal Negative Coverage$_{b,t-1}$	0.230**
	(0.084)
Observations	73,709
R^2	0.775
Panel B	
Abnormal Searches$_{b,t-1}$	0.081***
	(0.022)
Abnormal Negative Coverage$_{b,t-1}$	0.230***
	(0.072)
Observations	73,709
R^2	0.775
Additional Controls (Panels A and B)	
Brand FE	Yes
Bank-Week FE	Yes
Product-Week FE	Yes

Notes: This table reports the results of OLS panel regressions. The dependent variable *Deposit Rate*$_{b,d,t}$ is the rate offered by deposit brand b for deposit d with minimum deposit amount of £10,000 during week t, in percentage points. *Abnormal Searches*$_{b,t-1}$ is the log Google search volume for brand name b, minus the log search volume over the past 8 weeks. *Abnormal Negative Coverage*$_{b,t-1}$ is the net fraction of negative words in newspaper articles about a bank/brand, summed by bank/brand and week, minus the log search volume over the past 8 weeks. The sample includes all Sterling adjustable-rate onshore deposit products offered by all UK-headquartered commercial banks and building societies from 2007q1 to 2015q1, except building societies with less than 15 branches. Standard errors are clustered by bank. Stars indicate significance at 1 (***), 5 (**) and 10% (*) confidence level, respectively.

Table 14: DEPOSIT RATES AND ABNORMAL SEARCHES: CONTROLLING FOR NEWS: THE ROLE OF DEPOSIT INSURANCE

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent Variable: *Deposit* $Rate_{b,j,d,t}$					
$\text{Uninsured}_{j,t}$	1.19***	1.18***	1.54	0.64	0.75	0.64
	(0.38)	(0.37)	(2.23)	(0.98)	(1.64)	(2.00)
$\text{Abnormal Searches}_{b,t-1}$		0.31**	0.91*			
		(0.11)	(0.53)			
$\text{Uninsured}_{j,t}$ x $\text{Abnormal Searches}_{b,t-1}$		0.57*	0.87***	077***	0.59*	0.68**
		(0.32)	(0.30)	(0.24)	(0.29)	(0.29)
$\text{Uninsured}_{j,t}$ x $\text{Abnormal Searches}_{b,t-1}$ x $\text{Retail Funding}_{i,t}$			-0.79*	-1.86***	-1.40**	-1.65**
			(0.46)	(0.23)	(0.56)	(0.60)
$\text{Retail Funding}_{i,t}$			-1.32*			
			(0.68)			
$\text{Retail Funding}_{i,t}$ x $\text{Abnormal Searches}_{b,t-1}$			-0.75			
			(0.62)			
$\text{Uninsured}_{j,t}$ x $\text{Retail Funding}_{i,t}$			-0.49	-1.30	-1.03	-0.94
			(2.76)	(1.20)	(2.13)	(2.36)
Observations	145,726	145,726	145,726	145,646	96,483	96,483
R^2	0.04	0.04	0.06	0.63	0.79	0.79
Jurisdiction FE	Yes	Yes	Yes	Yes	Yes	Yes
Brand-Week FE				Yes		
Brand-Week-Product FE					Yes	Yes
Offshore-Week FE						Yes

Notes: This table reports the results of OLS panel regressions. The dependent variable *Deposit* $Rate_{b,j,d,t}$ is the rate offered by deposit brand b in jurisdiction j for deposit product d with minimum deposit amount of £10,000 during week t, in percentage points. $Uninsured_{j,t}$ is 1 in a jurisdiction and time period where a £10,000 deposit is covered by deposit insurance, and 0 otherwise. *Abnormal* $Searches_{b,t-1}$ is the log Google search volume for brand name b, minus the log search volume over the past 8 weeks. *Retail* $Funding_{i,t}$ is the share of the bank's total liabilities in the form of deposits by individuals. The sample includes all Sterling adjustable-rate onshore and offshore deposit products offered by all UK-headquartered commercial banks and building societies from 2007q1 to 2015q1, except building societies with less than 15 branches. Standard errors are clustered by bank. Stars indicate significance at 1 (***), 5 (**) and 10% (*) confidence level, respectively.