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Abstract: We use a conjoint analysis of 551 subjects to compare the reaction of finance professionals to news of a banking crisis with the reactions of non-finance professionals and graduate students. All three groups make greater deposit withdrawals if deposit insurance protection involves a haircut, but the response of finance professionals is more nuanced: compared to non-finance professionals and students, they seem to care about haircuts mainly when bank capitalization is low and less so when capitalization is high. Both finance and nonfinance professionals are more concerned about the pre-funding of deposit insurance than are students. Overall though, the greater banking sector knowledge and experience presumably possessed by finance professionals does not seem to automatically translate into significantly different crisis-response behavior.

Keywords: Banking crisis, Finance professionals, Deposit withdrawals

JEL Classifications: G21; G28

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Depositor Responses to a Banking Crisis: Are Finance Professionals Special?

1. Introduction

Deposits represent the largest funding source for commercial banks. But, as is well known, they also can be an unstable source: The theoretical models of Diamond and Dybvig (1983) and Goldstein and Pauzner (2005) show how uninsured depositors can rationally take flight during a banking crisis, while Goldsmith-Pinkham and Yorulmazer (2010), Iyer and Puri (2012), Iyer et al. (2016), and Martin et al. (2018) document recent examples of actual bank runs. What is less well known, however, is whether deposit withdrawal decisions during a banking crisis differ systematically between depositor types. In particular, does the response of those working in financial markets ("finance professionals") differ from the response of other, possibly less informed, depositors, and if so, how? As well as being of intrinsic interest, answers to these questions can help design better informed, and better targeted, banking policies.

Theoretically, the crisis response by finance professionals *vis-a-vis* other types of depositor is ambiguous. On the one hand, the finance professionals' (presumably) deeper understanding of the business of banking may cause them to respond more quickly to news of a potential crisis.[1] On the other hand, their (presumably) greater familiarity with the banking industry and regulatory environment may make them less inclined to panic on the receipt of such news, particularly when bank deposit accounts are protected by deposit insurance.

To address the issue, we employ a conjoint analysis of 551 subjects drawn from three distinct groups: finance professionals, other professionals who work in the finance industry in support tasks ("non-finance professionals"), and graduate students. Subjects are shown a series of bank deposit accounts that differ in size and along multiple dimensions capturing the risk of loss, including the level of bank capital and several deposit insurance features

[1] While their crisis-driven personal banking decisions are less explored, finance professionals are known to withdraw funds at the first indication of a crisis in the wholesale bank funding market (Huang and Ratnovski, 2011); examples of such withdrawal propensity are discussed by Afonso et al. (2011), Covitz et al. (2013), and Boissel et al. (2017), among others.

(e.g., guaranteed payout percentage and pre-funding), and then told to put themselves in the shoes of the depositor and report their reaction to the hypothetical collapse of a large national bank that could potentially affect the viability of the bank holding their deposit.[2] In particular, we ask our subjects to indicate what percentage of the account balance, if any, they intend to withdraw, after taking into consideration the anticipated deposit interest rate decision by bank management. Our approach allows us to distinguish the crisis response of finance professionals from that of other depositors. Comparing finance with non-finance professionals isolates the importance of experience in performing financial tasks; comparing non-finance professionals with students isolates the importance of experience in the finance industry, irrespective of task.

Overall, our results suggest that finance professionals respond to news of a banking crisis similarly to non-finance professionals and students. All three subject groups demonstrate at least a basic understanding of the risk trade-offs involved. Regardless of group, withdrawal decisions depend primarily on deposit risk of loss: The withdrawal rate of every group increases with the size of the deposit haircut to be potentially applied in the event of bank failure. Moreover, all groups reduce their intended withdrawals when deposit insurance pre-funding is present.

Nevertheless, we also observe some differences between the groups. In particular, finance professionals seem to view the interaction between the potential haircut and bank capitalization differently. When the level of bank capital is below average, haircut potential has a large and homogenous effect on the withdrawal decisions of the three groups, e.g., all else equal, a 33% haircut raises intended withdrawal rates by 28.2 percentage points (p.p.) among finance professionals, and by 25.4 p.p. and 25.5 p.p. among non-finance professionals and students respectively. However, when the capital level is above average, haircuts not only matter less, but do so in a heterogenous manner: a 33% haircut raises withdrawal rates by 11.8 p.p. and 12.1 p.p. among non-finance professionals and students respectively, but by only 5.8 p.p.

[2] We explicitly link the onset of the hypothetical banking crisis to the collapse of a large national bank. In actual historical data, identifying the exact onset and nature of a crisis (e.g., banking vs. financial), and distinguishing it from the government's response, can be problematic (e.g., Boyd et al., 2019; Baron et al., 2021).

among finance professionals. Thus, in contrast to the other two groups, finance professionals seem to care about haircuts mainly when bank capital is relatively low.

Also, the extent to which deposit insurance pre-funding can help mitigate withdrawals in a banking crisis differs across the subject groups. Holding all else equal, both finance and non-finance professionals decrease their withdrawals in the presence of pre-funding (by 11.1 and 12.0 p.p. respectively) by significantly more than do graduate students (6.2 p.p.); whether pre-funding exists matters more to the professional groups than to students.

Our paper links two emerging themes in the literature. First, some recent work investigates potential heterogeneity in investor behavior while focusing on the actions of finance professionals. For example, Bodnaruk and Simonov (2015) find little evidence that mutual fund managers make better equity investment decisions than matched peers who lack financial expertise, though managers seem to be more knowledgeable about available financial opportunities in general. Agarwal et al. (2017) show that finance professionals are less likely to default on their mortgage than other borrowers. Holzmeister et al. (2020) detect no significant differences in risk assessment and related behavior between finance professionals and lay individuals. Experimentally, Cohn et al. (2017) demonstrate that bank employees display increased risk aversion in their professional capacity but employees in other industries do not, while Kirchler et al. (2018) document a strong link between non-monetary job performance incentives and risk-taking by finance professionals, which is absent in the case of other individuals. Also, Kirchler et al. (2020) suggest that finance professionals are more driven by the desire to outperform competing investors than the general public. However, none of these papers considers personal banking decisions.

Second, Iyer and Puri (2012), Iyer et al. (2016), and Iyer et al. (2019) use bank micro-data to examine banking decisions and find that the propensity to run is related to, among other factors, education, gender, wealth, income, and financial literacy. However, these studies do not compare the decisions of financial professionals with those made by other depositor types.[3] Our paper extends the investor heterogeneity focus of the first theme to

[3]Available bank micro-data are not quite finely grained enough to distinguish between finance professionals and other types of depositor.

the personal banking focus of the second theme.

The next section describes our research methodology and data collection. Section 3 provides descriptive statistics. Section 4 outlines our econometric approach and discusses estimation results and their implications. Section 5 offers concluding remarks.

2. Research Methodology and Data Collection

Described in broad terms, our research design has two components. First, using a conjoint analysis approach, we collect data on how three distinct subject groups—finance professionals, non-finance professionals, and graduate students—respond as individual depositors to a hypothetical banking crisis. Second, we analyze the collected data to determine whether these responses systematically differ with regard to the subject type as well as to pinpoint the source(s) of any such differences. In this section, we outline key features and advantages of conjoint analysis and provide details on the development of our data collection instrument and the subject recruitment and data collection procedures. Our data analysis strategy based on an econometric model is described in section 4.1.

2.1. Conjoint Analysis Approach

The standard conjoint analysis approach is a multi-attribute preference measurement technique that seeks to determine how much certain attributes of a product or service matter to consumers.[4] It involves presenting a series of hypothetical product profiles to a sample of subjects and then asking them to rank these profiles according to a specified criterion. The underlying idea is that responses implicitly reveal relative preferences across different profile attributes, and that the trade-offs involved can be quantified using standard data analysis methods, including regression analysis. This approach, and its variants, has been applied in a wide variety of settings: for example, evaluating multi-part pricing designs for cell phones (Iyengar et al., 2008), determining brand equity effects on consumer willingness to pay (Ferjani et al., 2009), predicting the effects of marketing policy changes on pharmaceutical

[4] Green and Wind (1975) provide an introduction to conjoint analysis. Recent expositions can be found in Netzer and Srinivasan (2011) and Aribarg et al. (2017).

firms (Kappe et al., 2017), and assessing the value of different aspects of an advertising campaign (Bertrand et al., 2010).

For our purposes, the use of conjoint analysis has several advantages. Compared to historical data on depositor behavior, the conjoint approach is more feasible, less prone to error, and more flexible. Real-world data on individual depositors across multiple banks are difficult to obtain, are unlikely to contain sufficient information at the individual depositor level (e.g., identifying finance professionals is likely to be a noisy process), and present the researcher with difficulties in distinguishing the effects of variables of interest from a myriad of confounding phenomena. Furthermore, historical data permit consideration only of institutional settings and policies that have actually existed, whereas the conjoint approach allows us to investigate settings that have existed as well as those that may be of interest to policy-makers and regulators but have not yet been implemented in practice. As such, the approach gives us flexibility with regard to the choice of deposit insurance features to study and, in particular, permits us to assess how different degrees of insurance coverage can affect depositor reactions in a banking crisis.[5]

In comparison to a typical laboratory experiment that would allow for only one attribute change at a time, conjoint analysis more readily enables an assessment of simultaneous changes in several profile attributes (such as different deposit insurance and bank account characteristics). It also allows us to obtain responses from a heterogeneous sample of bank customers at a low cost. In contrast to standard survey approaches, which rely on subjects' recall of past behavior, conjoint analysis produces results that are less susceptible to social desirability and retrospection biases: because all scenarios are hypothetical, subjects need not be swayed by the possible social consequences of their crisis-induced behavior, or misremember decisions made in the (possibly distant) past. Overall, the conjoint analysis approach aims to combine the internal validity of a laboratory experiment with the external validity of a survey.

[5]This contrasts with field data studies that are only able to distinguish between fully- and less-than-fully-insured deposits, e.g., Iyer and Puri (2012), Acharya and Mora (2015), Iyer et al. (2016), Egan et al. (2017), Lambert et al. (2017), Martin et al. (2018), and Iyer et al. (2019).

The conjoint analysis approach has its limitations. In particular, it imposes orthogonality across profile attributes and, thus, does not allow us to study interactions among them. In addition, tractability requires the set of profile attributes investigated to be modest in size and the number of possible values of each attribute to be small. And, of course, it considers a hypothetical crisis.

2.2. Data Collection Instrument

2.2.1. Setup and Instructions to Subjects

We wish to measure how different bank customers would react to news of a banking crisis as holders of deposit accounts with varying degree of depositor protection. For this purpose, we develop a data collection instrument that invites subjects to put themselves in the shoes of holders of eight hypothetical bank accounts (i.e., "account profiles") at the onset of a hypothetical banking crisis and report their predictions and intended behavior with regard to each such account profile. The instrument shows subjects one profile at a time and asks them to provide their (profile-specific) responses to our questions before moving on to the next profile. The eight account profiles are differentiated along attributes listed in Table 1; the definitions of the attributes are included in the instrument and also made available to subjects on a reference card. After collecting responses for every account profile, the instrument asks subjects to report their demographic and socioeconomic personal characteristics (e.g., age, gender, and financial net worth.)

We specify the onset of the hypothetical banking crisis by informing subjects that a large bank has just failed and that this event has raised the likelihood of financial difficulties for the particular bank in which each subject is a depositor. Because subjects may hold a wide array of (unobserved) beliefs about the hypothetical economic environment at the beginning of the data collection exercise, it is possible that the preconceived beliefs of different subject groups about aspects of the environment relevant for depositor decision-making (e.g., how likely the government is to rescue the subject's bank) differ systematically, which could skew responses to our questions and distort inference. In an attempt to prevent this, we instruct subjects to make a number of assumptions about the environment, namely: (1) prices will remain stable for at least one year, (2) taxes are not a relevant consideration, (3) they have no deposits at another bank, (4) their bank is not considered "too big to fail," (5) the country's deposit insurance agency will not fail, (6) any failed bank would be closed promptly, and (7) their bank has no direct government ownership.[6]

The next section provides details on the specification of the bank account profiles and explains why we have eight of them in total. The following section discusses questions asked of subjects regarding each profile and resulting response variables.

2.2.2. Bank Account Profiles

We define profiles in terms of five attributes: maximum deposit insurance coverage per deposit ($250,000 or $100,000), relative deposit size (75%, 100%, or 150% of the maximum insurance coverage amount), co-insurance provision (75% or 100% guaranteed payout up to the maximum insurance coverage amount), pre-funding of deposit insurance (yes or no), and bank capital level (above or below average in the banking system).[7] The definitions of these attributes are provided in Table 1.

Ideally, we would also like to include additional bank characteristics such as size and liquidity, but even with the above relatively small number of attributes, the number of possible combinations, and hence profiles, equals 48 ($2 \times 3 \times 2 \times 2 \times 2$), which is infeasibly large. We therefore employ the fractional-factorial design algorithm in the SPSS conjoint module to whittle the number of profiles down to eight; this reduces the cognitive burden on subjects, but at the same time allows us to capture essential trade-offs between the various account attributes.

Table 2 describes these eight profiles and indicates the information provided to subjects at the time of data collection. Accounts 1, 4, 5, and 7 offer deposit insurance coverage up to a maximum of $100,000 per deposit; for accounts 2, 3, 6, and 8, the coverage limit is

[6] Section 4.1 describes additional econometric steps we take to help account for any systematic differences in subject beliefs.

[7] Egan et al. (2017) document changes made in 2008 and in the Dodd-Frank Act of 2010 to the FDIC insurance coverage and highlight a critical role played by the insurance limit and bank capital requirements in promoting the stability of a banking system. Qi et al. (2020) incorporate the existence of co-insurance into their measure of deposit insurance coverage intensity when explaining deposit flows. IADI (2009) discusses differences between ex ante and ex post deposit insurance system funding approaches.

\$250,000. The deposit sizes in accounts 5 and 6 are exactly equal to the respective coverage limits, in accounts 1, 2, 3, and 7 they are 75% of the limits, while in accounts 4 and 8 they equal 150% of the limits. Accounts 1, 6, 7, and 8 are subject to co-insurance, while the remaining accounts are not. The net effect of these attributes is that deposits in accounts 2, 3, and 5 will be paid back in full if the bank fails, while the remainder offer varying degrees of less-than-full protection; to capture this idea in a single variable, we define *Fraction at risk* as the difference between 100% and the percentage of deposit that will be paid back in the event of bank failure, given the coverage limit and co-insurance provisions. For example, in the case of account 1, which features a deposit of $(0.75) \cdot \$100,000 = \$75,000$, the deposit insurer must pay $min[(0.75) \cdot \$75,000; \$100,000] = \$56,250$, which comprises $(\$56,250/\$75,000) \cdot 100\% = 75\%$ of the deposit. Thus, the "fraction at risk" in this case is 25%. Accounts 1, 3, 5, and 8 are held at banks that contribute to a deposit insurance fund, while the remaining accounts are held at banks that do not. Finally, accounts 1, 3, 4, and 6 are held at banks with relatively high capital, while the remainder are held at banks with relatively low capital. Overall, the structure of these profiles forces subjects to consider a number of trade-offs among the various account attributes.

2.2.3. Questions for Subjects and Response Variables

Every subject was asked two questions about each account profile:

Question 1: "On hearing about the shock to the banking system, I expect my bank to raise the deposit interest rate by..."

Question 2: "Given the increased risk of bank failure and expected interest rate change, what percentage of your deposit would you immediately withdraw?"[8]

Our primary interest is in responses to Question 2. The main purpose of Question 1 is to encourage subjects to think about their personal banking decisions in the context of a banking system crisis while recognizing that banks are also likely to be reacting to the crisis. We also use responses to Question 1 to infer information on unobserved subject beliefs about the hypothetical economic environment in order to account for the potential heterogeneity

[8]The list of response options to Questions 1 and 2 includes, among other options, "0 p.p." (i.e., no change in the interest rate) and "0%" (i.e., no withdrawal) respectively.

of such beliefs when estimating our econometric model of intended withdrawals; full details are provided in section 4.1.

To minimize subject fatigue and non-response, we asked subjects to select an answer from a given list of options rather than provide their own numerical response. For Question 1, they were offered choices in steps of 0.5 p.p., ranging from 0 to 5.5 p.p. or more. For Question 2, the available response options range from 0% to 100% in steps of 10%.

2.3. Recruiting Subjects and Collecting Data

We collect data from three subject groups that potentially differ in their knowledge of, and experience with, the United States banking system: finance professionals, non-finance professionals (i.e., professionals who work in the finance industry in support tasks), and graduate students. Subjects are required to reside in the United States as this avoids concerns that they may interpret questions in the context of different banking systems and institutional settings.[9]

To obtain data on finance and non-finance professionals, we identified a variety of relevant organizations such as banks, insurance companies, and accounting firms and contacted the executive management of these organizations to solicit their endorsement of the study to their employees in the hope of maximizing response rates. For confidentiality reasons, we are unable to disclose the identities of the organizations. We requested our initial contact in each organization that had agreed to engage in the study to identify finance and non-finance professionals separately in the employee pool, email prospective subjects in the organization a brief statement on the study's purpose and a link to the data collection instrument, and follow up with a reminder in about two weeks after the initial solicitation.[10]

While specific job titles vary, the finance professional subjects work in the investment division, provide financial planning solutions, or oversee financial market operations. Two typical descriptions of the type of work performed are:

> A cross section of accounting and finance professionals. The majority work either

[9] An obvious caveat in interpreting our results is that they may not be generalizable to depositor behavior in other countries.

[10] The instrument was hosted online and versioned so that we could track the group identity of a subject.

directly in the investment division or work closely with investment transactions on a daily basis. Experience levels range from 5 to 30 years.

Advisors who provide holistic financial planning solutions directly to customers, and work across the spectrum of insurance, risk management, investments, and retirement planning.

We define non-finance professionals as white collar employees not directly involved in financial decision-making. Examples of such roles include marketing, public relations, information technology, human resources, and legal. This designation recognizes subjects with less direct financial market exposure than that of finance professionals while allowing for the possibility of an industry effect unrelated to the subject's specific position within the organization.

In total, we collected usable data from 298 finance professionals and 157 non-finance professionals. Due to privacy issues, we had no direct access to employee email lists used by our contacts in the participating organizations. Thus, the response rate cannot be calculated precisely. However, based on the information communicated to us subsequently by organizations providing a large majority of subjects, we estimate that the response rate among finance professionals is approximately 26%.[11]

To recruit student subjects, we purchased an email directory from the university registrar at a public university and solicited responses from graduate students enrolled in any major. The data collection procedure is similar to that in the case of finance and non-finance professionals, except that we compiled the list of email addresses to send invitations and reminders to on our own.

In total, we obtained usable data from 96 graduate students. The response rate among students is approximately 8%. Given that this rate is less than a third of the rate among finance professionals, we followed the Armstrong-Overton (1977) procedure to assess whether non-response could substantially bias inference based on student data.[12] The procedure

[11] The participating organizations did not provide us with sufficient information to reliably estimate the response rate among non-finance professionals.

[12] The relatively high response rate among finance professionals (26%) could be due to the explicit en-

orders student subjects according to how promptly they answered our invitation and then tests for differences between the temporally-first and temporally-last quartiles. The assumption is that the least prompt subjects (i.e., last quartile) most resemble non-respondents (Armstrong and Overton, 1977; Viswesvaran et al., 1993). We find no statistically significant differences in the characteristics of the first and last quartiles, which suggests that non-responding students are unlikely to systematically differ from our student subjects.

The data collection exercise spanned 2016-2018 (with the bulk of data collected in 2018) and was reviewed and approved by the participating organizations' management and lawyers and declared exempt from the requirements of the human subject protections regulations by the public university's Institutional Review Board. We advertised an incentive of $10 in the form of a gift card for completing the data collection exercise and provided it to subjects on request. We calculate that among finance and non-finance professionals, approximately 27% requested and received the gift cards. Among graduate students, the fraction is 82%.

Our final sample consists of 551 subjects: 298 finance professionals, 157 non-finance professionals, and 96 graduate students. Other researchers have used samples of similar size in a range of experiments and surveys (e.g., Boyle et al., 2015; Cohn et al., 2015; Cohn et al., 2017; Kirchler et al., 2018).

3. Descriptive Statistics

3.1. Personal Characteristics

To better understand the composition of our subject sample, as part of the data collection exercise we obtained information on the age, gender, and wealth (measured by self-reported financial net worth) of subjects. Table 3 provides descriptive statistics for these personal characteristics. Panel A reports the distribution of each characteristic in each of the three subject groups. Panel B analyzes differences between the groups.

In general, finance professionals are older, more likely to be male, and wealthier than non-finance professionals, who in turn are older and wealthier than students.[13] All these

dorsement of our study by their employers.

[13]Nevertheless, almost 23% of student subjects report a net worth of $100,000 or more. This likely reflects the postgraduate, and hence older, nature of our student sample.

differences are statistically significant at the 1% level, with the exception of the gender difference between finance professionals and students, which is marginally significant at the 8% level.[14] Overall, the variation in group characteristics seems to correspond with reasonable priors about the underlying populations.

3.2. Crisis Responses

Table 4 summarizes the frequency distributions of responses to the expected interest rate change and intended withdrawal questions over all account profiles jointly. The crisis response of the subject groups is not monotonic in financial sector experience. Graduate students react most strongly to the news of the banking crisis, expecting both the largest interest rate change on average and intending to make the greatest withdrawal (mean of 47.0%). Finance professionals anticipate a slightly weaker bank response (in terms of the interest rate offered) compared to non-finance professionals, but intend to make a slightly greater average withdrawal for themselves (41.3% vs. 38.5%). The differences in the response distributions between the three subject groups are significant at the 0.3% level or better; Table 5 provides the details.[15]

Group responses at the ends of the withdrawal distribution vary somewhat. Consistent with the average outcomes, a smaller fraction of students (16.7%) plan to sit tight, compared with 25.7% and 30.0% of finance and non-finance professionals respectively. At the other extreme, however, the fraction that intend to withdraw their entire deposit does not change by much with depositor type, being approximately 15-16% in all three groups.

Figure 1 illustrates how subject responses differ across the account profiles. For all three subject groups, intended withdrawal fractions, as well as expected interest rate increases, are greatest for profiles 7 and 8, which are accounts held at banks with below-average capital, are subject to substantial haircuts, and (in the case of profile 7) do not contribute to an insurance

[14]The 42%-58% female-male split of the student group closely reflects the gender composition of the university's graduate student population.

[15]While they are not reported in the tables, we also performed tests of differences in the distributions of withdrawal responses between individual account profiles. The test results strongly reject (at the 1% significance level) a null hypothesis that withdrawals from different account profiles come from the same distribution, in both the full sample of subjects and also in each of the three subject groups.

fund. By contrast, profiles 3 and 5 are associated with much more subdued responses: both accounts are fully insured and held at banks contributing to an insurance fund.

Regardless of their type, our subjects seem to lack complete confidence in deposit insurance as they withdraw positive fractions from fully-insured accounts and more than just the uninsured fraction from partially-insured accounts. Similar behavior has also been observed in the field: Carlson and Rose (2016) find that the 1984 run on Continental Illinois continued even after the FDIC guaranteed all of the bank's liabilities, while Martin et al. (2018) report flight from both insured and uninsured deposits in a failing bank. This lack of confidence varies across depositor types, with students being the most skeptical. For example, the average intended withdrawal from the fully-insured account profile 5 ranges from 23.6% for non-finance professionals to 33.1% among students. Also, even though taking out 33% from account profile 4 would leave the remaining balance fully insured, the average intended withdrawal from this account ranges from 38.1% among finance professionals to 47.1% among students.

4. Regression Analysis

4.1. Econometric Model

Our objective is to understand how depositor reactions, in terms of intended withdrawals, to news of a banking crisis depend on depositor type. Inferring the effects of interest and interpreting estimates would be difficult if subjects formed different beliefs about relevant aspects of the hypothetical economic environment in the data collection exercise. In an attempt to ensure common beliefs and a uniform environment, we instructed all subjects to make a series of assumptions at the onset of the exercise. For instance, subjects were asked to assume that the deposit insurer would not fail; section 2.2.1 provides the list of the assumptions. However, it is infeasible to exhaustively specify the environment. While mentally "filling in the gaps" in the instructions, subjects could ultimately have formed different (unobserved) beliefs, both across the board and in the case of each individual profile, and incorporated such beliefs into their decision-making. The beliefs could vary by depositor type due to systematic differences in financial market exposure and experience, for example.

We address this using a two-pronged strategy. First, we include subject fixed effects in all estimated equations. The fixed effects can help account for possible differences across subjects in, for example, the interpretation of our description of the onset of a banking crisis, which could have led to varying perceptions of its severity. Furthermore, they can help prevent potential confounding from (profile-invariant) personal characteristics (e.g., age, gender, and net worth), some of which systematically differ between subject groups and can influence decision-making. Estimation results strongly support the existence of subject fixed effects (e.g., refer to the results of testing for joint non-significance of fixed effects in Table 6).

Second, we exploit the order, and structure, of the two questions asked in the case of each profile in order to facilitate more accurate inference.[16] In particular, we extract potentially relevant information from the answer about the interest rate change the subject expects his or her bank to implement following news of the crisis and then incorporate this information in the equation for intended withdrawal. The underlying idea is that the data collection layout could have prompted the subject to make profile-specific assumptions about the environment while answering the interest rate question and then draw on them when deciding on the percentage of deposit to withdraw. Such assumptions can vary across subjects.

We now formalize this strategy. For subject i, let N_i be 1 if i is a non-finance professional (0 otherwise) and S_i be 1 if i is a graduate student (0 otherwise); finance professionals are the baseline group. For account profile j, let p_j be the attribute vector of j, containing variables *Deposit size*, *Fraction at risk*, *Insurance fund*, and *Low bank capital*; Table 1 provides the definitions of these variables. Because below-average capital could have more relevance for individual decision-making when deposit is only partly, as opposed to fully, insured, we incorporate the interaction between the fraction at risk and low bank capital variables, *Fraction at risk* $\times$ *Low bank capital*, in p_{ij}.[17] Importantly, we interact the subject group indicators N_i and S_i with the profile attribute vector p_j and include interaction terms $N_i \times p_j$

[16] Recall that the withdrawal question followed, and was conditioned on, the interest rate question.

[17] Since *Fraction at risk* is a constructed index variable, the conjoint orthogonality restriction does not apply to it. Thus, we are able to use the interaction *Fraction at risk* $\times$ *Low bank capital* as an explanatory variable.

and $S_i \times p_j$ in estimated equations in order to allow for variation in the attribute effects by depositor type.

The initial step in our two-pronged strategy is to estimate the following equation for the interest rate response:

$$r_{ij} = p_j' \cdot \alpha_0 + (N_i \times p_j)' \cdot \alpha_N + (S_i \times p_j)' \cdot \alpha_S + v_i + \epsilon_{ij}, \tag{1}$$

where r_{ij} is the interest rate change anticipated by subject i in the case of profile j; α_0, α_N, and α_S are vectors of coefficients; v_i is a fixed effect; and ϵ_{ij} is an error term.

The error term ϵ_{ij} represents a portion of r_{ij} that cannot be attributed to the explanatory variables and fixed effects. Rather, it captures the impact of unobserved beliefs and assumptions of subject i pertaining to profile j; for example, how strongly the central bank would respond to the crisis and shore up i's bank in this particular scenario. Since such beliefs and assumptions are likely to influence decision-making about deposit withdrawal, we aim to account for ϵ_{ij} when modeling the withdrawal response. To be specific, we use equation (1) estimates (denoted below by $\hat{\alpha}_0$, $\hat{\alpha}_N$, etc.) to obtain an estimate of ϵ_{ij} as:

$$\hat{\epsilon}_{ij} = r_{ij} - p_j' \cdot \hat{\alpha}_0 - (N_i \times p_j)' \cdot \hat{\alpha}_N - (S_i \times p_j)' \cdot \hat{\alpha}_S - \hat{v}_i,$$

and then employ $\hat{\epsilon}_{ij}$ when estimating the following equation for the withdrawal response:

$$w_{ij} = p_j' \cdot \beta_0 + (N_i \times p_j)' \cdot \beta_N + (S_i \times p_j)' \cdot \beta_S + \hat{\epsilon}_{ij} \cdot \gamma_0 + N_i \times \hat{\epsilon}_{ij} \cdot \gamma_N + S_i \times \hat{\epsilon}_{ij} \cdot \gamma_S + u_i + \varepsilon_{ij}, \tag{2}$$

where w_{ij} is the percentage of deposit in account profile j that subject i intends to withdraw; β_0, β_N, and β_S are vectors of coefficients; γ_0, γ_N, and γ_S are scalar coefficients; u_i is a fixed effect; and ε_{ij} is an error term.[18]

We are interested mainly in the estimates of β_0, β_N, and β_S, which aim to capture the intended withdrawal decisions of finance professionals and any differences with non-finance professionals and students respectively. The difference between students and non-finance professionals can be calculated as $\beta_S - \beta_N$. Given that $\hat{\epsilon}_{ij}$ is an estimated, as opposed to observed, variable in equation (2), we obtain standard errors using a bootstrap procedure that employs 1,000 replications (with replacement) and accounts for the panel nature of the data. The estimation and bootstrap are implemented in Stata 14.

[18]The specification allows for the effect of $\hat{\epsilon}_{ij}$ to vary by depositor type.

4.2. Main Results

In section 3.2 (specifically, Tables 4 and 5), we found that, on average over all account profiles, news of the hypothetical banking crisis invokes the strongest intended withdrawal response among students, the weakest among non-finance professionals, with finance professionals falling somewhere in between; moreover, differences between the withdrawal response distributions of the three subject groups are strongly statistically significant. In this section, we aim to go a step further and identify the mechanisms by which the three subject types respond differently to the crisis. Specifically, we estimate equation (2) to determine whether, and how, the effects of account attributes on intended withdrawals differ across the subject types.

The results from estimating equation (2) appear in Table 6.[19] Before proceeding to discuss our principal findings, we note that the value of the within R^2, which may be more relevant for assessing the performance of a model with fixed effects than the overall R^2 (we report both R^2 values in the last row of the table), is 0.26, indicating that our model is able to explain more than a quarter of the variation in withdrawal responses.

We also are encouraged by detecting virtually no impact of the bank capital level on withdrawal responses in the absence of haircuts (i.e., when *Fraction at risk* = 0). Specifically, below-average capitalization (*Low bank capital* = 1) has no significant effect on the withdrawals of finance professionals or students and only a small positive effect of 6.6 p.p. ($-1.066 + 7.698$) among non-finance professionals. These outcomes are consistent with our directing subjects to assume that the deposit insurance agency would always deliver on its obligations to depositors of failed banks and that all such banks would be closed promptly. Thus, even though a bank may be under-capitalized and, as such, relatively likely to fail, its depositors face no risk of losing funds when deposit insurance provisions preclude a haircut and no risk of being stuck in a legal "limbo." If, on the contrary, we were to find that subjects did take a lot of notice of bank capitalization in the absence of haircuts despite our instructions, we would have little confidence in the reliability of the responses overall.

Our principal results are as follows. First, in banks with a healthy capital base (i.e.,

[19] Equation (1) estimation results are included in Table A.1 in the appendix.

when *Low bank capital* $= 0$), haircuts matter to everyone, but are about twice as important to non-finance professionals and students as they are to finance professionals. All else equal, raising the haircut fraction from, for example, 0% to 33% when a bank has above-average capital increases the average intended withdrawal among finance professionals by only 5.8 p.p. (0.33×17.44), but by 11.8 p.p. ($0.33 \times [17.44 + 18.46]$) among non-finance professionals and 12.1 p.p. ($0.33 \times [17.44 + 19.32]$) among students (significantly different from finance professionals at the 5% and 10% levels respectively).

Second, in banks with a weaker capital base (i.e., when *Low bank capital* $= 1$), haircuts matter more and are of similar importance to all groups. All else equal, raising the haircut fraction from, for example, 0% to 33% when a bank has below-average capital increases average intended withdrawal among finance professionals by 28.3 p.p. ($0.33 \times [17.44 + 68.28]$), and by 25.4 p.p. ($0.33 \times [17.44 + 18.46 + 68.28 - 27.13]$) for non-finance professionals and 25.5 p.p. ($0.33 \times [17.44 + 19.32 + 68.28 - 27.81]$) for students; additional testing (not reported in Table 6) indicates that all inter-group differences in this case are statistically insignificant at conventional levels.

Taken together, the two results above have the following implications. First, haircuts are more of a concern to depositors when bank capital is lower, i.e., when failure is more likely.[20] Second, and more interestingly, attitudes towards haircuts differ substantially across groups: the impact of a given haircut on average withdrawal is more responsive to the level of bank capital in the case of finance professionals than in the case of the other two groups. For example, the effect of the 33% haircut on average withdrawal among finance professionals is almost five times as great when bank capital is below average relative to when capital is above average (28.3 p.p. compared to 5.8 p.p.), but only about twice as great among non-finance professionals and students (25.4 vs. 11.8 p.p. for non-finance professionals and 25.5 vs. 12.1 p.p. for students). Finance professionals seem to primarily care about the potential for a haircut when that potential is high (i.e., when bank capital is below average), whereas

[20] This is consistent with the finding of Egan et al. (2017, Table 2) that a higher probability of default causes a bank to decrease its market share of uninsured deposits relative to its market share of insured deposits.

non-finance professionals and students care about such potential even when it is low.

Third, deposit insurance pre-funding matters to everyone, but more so to professionals (both finance and non-finance) than to students. All else equal, its presence lowers intended withdrawals of finance professionals and non-finance professionals by 11.1 and 12.0 p.p. $(-11.12 - 0.902)$ respectively, but only by 6.2 p.p. $(-11.12 + 4.943)$ in the case of students (significantly different from both other groups at the 5% level). The apparently mitigating impact of pre-funding on withdrawals could relate to concerns about the speed of payouts after a forced bank closure, which pre-funding may be seen as partly mitigating.

Fourth, the effect of deposit size is negligible and differs little across the three subject types. What apparently matters to each type is the extent to which a deposit is perceived to be protected via pre-funding and the absence of a haircut, rather than the deposit size itself.

Finally, coefficient estimates for the residual from the interest rate change equation indicate that profile-specific beliefs that lead to inexplicably high interest rate forecasts also result in greater withdrawals. While the residual seems to play a bigger role in the case of finance professionals compared to the other two groups, the differences are significant at only the 10% level, which suggests that the impact is relatively uniform.

4.3. Runs

Our analysis in section 4.2 reveals some differences between the subject types in the context of the average withdrawal rate that they indicate in response to a hypothetical banking crisis. From a policy perspective, an equally-interesting issue concerns the propensity of subjects to "run" on a bank, i.e., to make large withdrawals. Following Iyer et al. (2016), we introduce a new dependent variable set equal to 1 if the intended withdrawal amount exceeds 75% and equal to 0 otherwise. We then re-estimate equation (2) using a fixed-effects logit model applied to this binary dependent variable.[21]

Table 7 reports marginal effects associated with each account profile attribute, as implied by the estimated model. A marginal effect is the change in the probability of a greater-than-

[21] Our econometric approach is based on Chamberlain (1980).

75% withdrawal if the corresponding attribute increases by one unit.[22] To contextualize the magnitude of these effects, the table also provides the "propensity to run," which is the fraction of withdrawals exceeding 75% among all intended withdrawals. We note that for both professional groups, the propensity to run is around 22%, but approaches 27% for students, a difference that is significant at the 5% level. All else equal, students are more likely to run than the other subject groups.

Turning to the marginal effects, the Table 7 estimates of inter-group differences differ somewhat from those in Table 6. First, regardless of subject type, a haircut significantly increases the probability of a run on a bank with below-average capital, but has no effect in the case of better-capitalized banks. Second, insurance pre-funding substantially lowers the probability of a run in a manner that is statistically indistinguishable across the three groups. Third, subjects who anticipate a strong bank interest rate response are more likely to run, an effect that again does not vary significantly by depositor type. In short, the variation across the three groups largely disappears: account profile attributes affect each group's propensity to run in a similar manner.

5. Concluding Remarks

Our conjoint analysis of depositor decision-making suggests that finance professionals respond similarly to non-finance professionals and graduate students when confronted with news of a banking crisis. All three groups are more inclined to withdraw deposits if deposit insurance protection involves a haircut and are less inclined to withdraw deposits if insurance pre-funding exists. Thus, from the perspective of a banking regulator, both deposit insurance generosity (haircut size) and structure (pre-funding) can matter when it comes to mitigating deposit withdrawals and preventing bank runs in a banking crisis. Although finance professionals' more nuanced response to the interaction between haircuts and bank capitalization seems more consistent with rational risk management than the simpler responses of non-finance professionals and graduate students, it could also just reflect intrinsic differences

[22]We evaluate marginal effects at the means of explanatory variables, while setting the fixed effect value to zero.

between subject groups not fully accounted for by fixed effects. Overall, the greater banking sector knowledge and experience presumably possessed by finance professionals does not seem to automatically translate into significantly different crisis-response behavior.

Whether or not any of these results generalize to non-crisis situations and other countries remains an open question. Nor are we able to shed light on depositor behavior in broader financial crises extending beyond the banking sector, or on the moral hazard incentives that potentially cause such crises. Finally, of course, our results are, by construction, artifacts of hypothetical bank accounts in a hypothetical crisis; it is possible that an actual bank crisis may elicit somewhat different behavior.

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Table 1: Glossary of Variables

This table provides the definitions of key variables.

Variable	Description
Profile attributes:	
Coverage limit	The maximum amount that a subject can claim from the deposit insurer if the bank fails; equals either \$100,000 or \$250,000.
Deposit as % of coverage limit	Size of the deposit specified as a percentage of the coverage limit; equals either 75% or 100% or 150%.
Maximum guaranteed payout	The percentage of the deposit, equaling either 75% or 100%, that will be paid back to the depositor if the bank fails, subject to the condition that such payout cannot exceed the coverage limit.
Insurance fund	Equals 1 if the bank contributes to an insurance fund that can be used to pay back depositors of failed banks, 0 otherwise.
Low bank capital	Equals 1 if the bank's capital/total assets ratio is below the average value of this ratio for comparable banks, 0 otherwise.
Additional variables constructed using profile attributes:	
Deposit size	The dollar value of the deposit (measured in \$100,000).
Fraction at risk	The difference between 100% and the percentage of deposit that will be paid back in the event of bank failure, given the coverage limit and co-insurance provisions.

Table 2: Bank Account Profiles

This table describes the eight bank account profiles used in our conjoint analysis. Each profile has five attributes. Coverage limit is the maximum amount that a subject can claim from the deposit insurer if the bank fails; it equals either $100,000 or $250,000. Deposit as % of coverage limit is the size of the deposit specified as a percentage of the coverage limit; this has three options: 75%, 100%, or 150%. Maximum guaranteed payout is the percentage of the deposit, equaling either 75% or 100%, that will be paid back to the depositor if the bank fails, subject to the condition that such payout cannot exceed the coverage limit. Insurance fund refers to whether or not the bank contributes to an insurance fund that can be used to pay back depositors of failed banks. Low bank capital refers to whether or not the bank's capital/total assets ratio is below the average value of this ratio for comparable banks. Deposit size is the dollar value of the deposit. Fraction at risk is the difference between 100% and the percentage of deposit that will be paid back in the event of bank failure, given the coverage limit and co-insurance provisions.

	Bank Account Profile							
Attribute	1	2	3	4	5	6	7	8
Information provided to subjects:								
Coverage limit	$100,000	$250,000	$250,000	$100,000	$100,000	$250,000	$100,000	$250,000
Deposit as % of coverage limit	75%	75%	75%	150%	100%	100%	75%	150%
Maximum guaranteed payout	75%	100%	100%	100%	100%	75%	75%	75%
Insurance fund	Yes	No	Yes	No	Yes	No	No	Yes
Low bank capital	No	Yes	No	No	Yes	No	Yes	Yes
Implied information:								
Deposit size	$75,000	$187,500	$187,500	$150,000	$100,000	$250,000	$75,000	$375,000
Fraction at risk	25%	0%	0%	33%	0%	25%	25%	33%

Table 3: Personal Characteristics of Subjects

Panel A shows the distributions of values of age, gender, and financial net worth in the groups of finance professionals, non-finance professionals, and graduate students. Panel B reports the results of Pearson's χ^2 tests of the null hypothesis that the distributions are identical between two indicated groups (p-values are in parentheses). For example, the "Non-finance pros. vs. finance pros." column lists statistics from a comparison of non-finance to finance professionals. The sample includes 298 finance professionals, 157 non-finance professionals, and 96 students.

Panel A: Breakdown of subject groups by values of indicated personal characteristic, %

Characteristic	Finance pros.	Non-finance pros.	Students
Age:			
20–30 years	10.10	20.38	76.04
31–40 years	22.82	26.11	16.67
41–50 years	24.16	22.29	5.21
Over 50 years	42.92	31.21	2.08
Gender:			
Female	30.54	44.59	41.67
Male	69.46	55.41	58.33
Net worth:			
Under \$100,000	14.09	27.39	77.08
\$100,000–\$500,000	32.55	37.58	18.75
\$500,000–\$1 million	26.17	19.75	3.13
\$1–5 million	23.83	14.65	0.00
Over \$5 million	3.36	0.64	1.04

Panel B: Results of testing for differences in distributions of personal characteristics' values

Characteristic	Non-finance pros. vs. finance pros.	Students vs. finance pros.	Students vs. non-finance pros.
Age:			
Pearson's χ^2 statistic	12.63	172.29	82.90
(p-value)	(0.013)	(0.000)	(0.000)
Gender:			
Pearson's χ^2 statistic	10.45	5.05	0.21
(p-value)	(0.005)	(0.080)	(0.649)
Net worth:			
Pearson's χ^2 statistic	19.60	145.62	65.19
(p-value)	(0.001)	(0.000)	(0.000)

Table 4: Frequency Distributions of Subject Responses

This table reports the frequency distributions of subject responses in the groups of finance professionals, non-finance professionals, and graduate students. Responses to the interest rate question *"On hearing about the shock to the banking system, I expect my bank to raise the deposit interest rate by"* are reported in percentage points (p.p.). The frequency distributions of these responses are provided in panel A. Responses to the intended withdrawal question *"Given the increased risk of bank failure and expected interest rate change, what percentage of your deposit would you immediately withdraw?"* are reported as a percentage (of the deposit balance); their frequency distributions are provided in panel B. In each case, we also show the mean, number of completed (i.e., non-missing) responses, and number of subjects.

Panel A: Interest rate change responses

Response (p.p.)	Frequency, %		
	Finance pros.	Non-finance pros.	Students
0	29.66	27.39	16.02
0.5 – 2.0	44.87	45.54	37.50
2.5 – 3.5	16.66	15.76	22.91
4.0 – 5.0	4.91	7.80	15.24
5.5 or more	2.22	2.23	7.68
Missing	1.68	1.27	0.65
Mean (p.p.)	1.41	1.52	2.29
# completed	2,344	1,240	763
# subjects	298	157	96

Panel B: Intended withdrawal responses

Response (percentage)	Frequency, %		
	Finance pros.	Non-finance pros.	Students
0	25.67	30.02	16.67
10 – 40	28.90	29.70	31.25
50	15.73	11.62	11.46
60 – 90	14.13	12.27	25.65
100	14.89	16.24	14.71
Missing	0.67	0.16	0.26
Mean (percentage)	41.27	38.51	47.01
# completed	2,368	1,254	766
# subjects	298	157	96

Table 5: Differences Between Distributions of Subject Responses

This table provides the results of testing for differences in the distributions of responses to the interest rate question (*"On hearing about the shock to the banking system, I expect my bank to raise the deposit interest rate by"*) and intended withdrawal question (*"Given the increased risk of bank failure and expected interest rate change, what percentage of your deposit would you immediately withdraw?"*) between indicated subject groups. For example, the "Non-finance pros. vs. finance pros." column lists test statistic values and p-values from comparisons of non-finance to finance professionals. We employ Pearson's χ^2 test, in which the null hypothesis is that distributions are identical, and report test statistic values (p-values are in parentheses).

	Non-finance pros. vs. finance pros.	Students vs. finance pros.	Students vs. non-finance pros.
Responses to interest rate question:			
Pearson's χ^2 statistic	28.59	225.89	118.88
(p-value)	(0.003)	(0.000)	(0.000)
Responses to intended withdrawal question:			
Pearson's χ^2 statistic	39.80	95.61	96.53
(p-value)	(0.000)	(0.000)	(0.000)

Table 6: Estimated Deposit Withdrawal Equation with Subject Fixed Effects

This table reports the results of estimating the intended deposit withdrawal model with subject fixed effects. Column (1) lists coefficients β_0 and γ_0 in equation (2), each of which represents the average percentage reduction in deposit size among finance professionals (the baseline subject group) following a 1-unit increase in a corresponding explanatory variable. Column (2) presents coefficients β_N and γ_N on the interactions between the explanatory variables and indicator for a non-finance professional; they show the difference in effect magnitudes between non-finance and finance professionals. Column (3) lists coefficients β_S and γ_S on the interactions between the explanatory variables and indicator for a graduate student; they show the difference in effect magnitudes between students and finance professionals. Column (4) provides the calculated difference in the effect magnitudes between students and non-finance professionals, as implied by the coefficients in columns (3) and (2). The estimation employs linear panel data regression methods and uses $4,343$ completed withdrawal answers from 551 subjects. Bootstrapped standard errors (based on $1,000$ replications) are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels respectively.

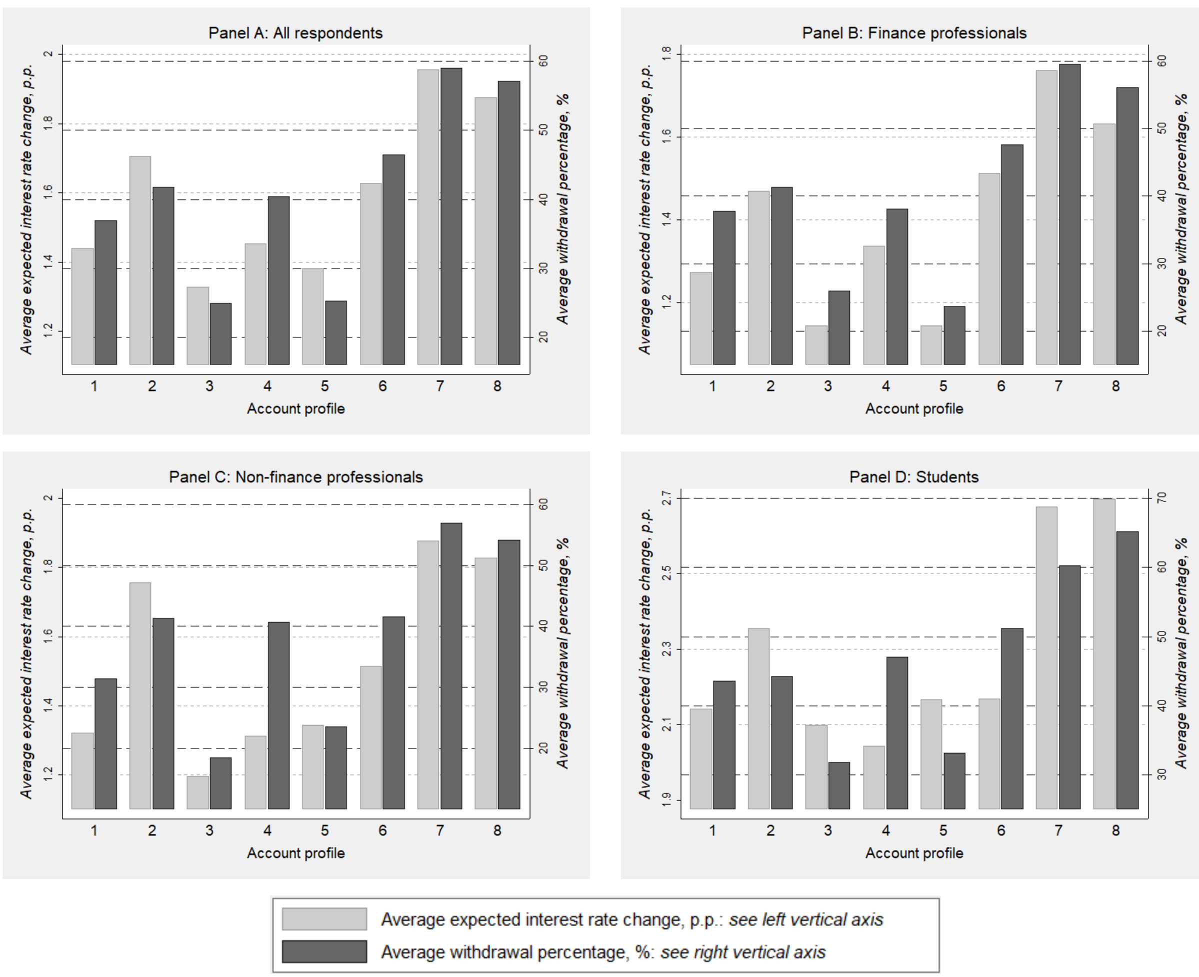
Explanatory variable	(1) *Baseline:* Finance pros.	(2) *Increment:* Non-finance pros. – finance pros.	(3) *Increment:* Students – finance pros.	(4) *Increment:* Students – non-finance pros.
Deposit size (in \$100K)	0.355	0.370	1.215	0.844
	(0.46)	(0.74)	(0.94)	(1.01)
Fraction at risk	17.44***	18.46**	19.32*	0.862
	(5.95)	(9.29)	(11.36)	(11.65)
Insurance fund	-11.12^{***}	-0.902	4.943**	5.845**
	(1.18)	(2.01)	(2.14)	(2.52)
Low bank capital	-1.066	7.698***	4.412	-3.286
	(1.51)	(2.44)	(2.79)	(3.02)
Fraction at risk × Low bank capital	68.28***	-27.13^{**}	-27.81^{**}	-0.683
	(7.34)	(12.08)	(13.93)	(15.00)
Residual from r_{ij} equation	9.090***	-3.327^{*}	-3.187^{*}	0.140
	(1.10)	(1.74)	(1.86)	(1.97)
H_0: All explanatory variable coefficients are jointly non-significant			F-statistic = 72.47 (p-value = 0.000)	
H_0: All fixed effects are jointly non-significant			F-statistic = 8.54 (p-value = 0.000)	
R^2-within (R^2-overall)			0.2568 (0.1294)	

Table 7: Marginal Effects in Estimated Logit Model of Propensity to Run with Subject Fixed Effects

This table shows the results from a logit model with subject fixed effects in which the dependent variable equals 1 if the intended withdrawal percentage exceeds 75% (0 otherwise); such withdrawal is intended to capture a bank run. Column (1) lists the explanatory variables' marginal effects (MEs) specific to finance professionals (the baseline subject group). An ME represents the change in the propensity to run following a 1-unit increase in the explanatory variable; it is calculated at the means of the explanatory variables while setting the fixed effect value to zero. Columns (2), (3), and (4) provide the difference in the magnitudes of MEs between non-finance and finance professionals, students and finance professionals, and students and non-finance professionals respectively. Bootstrapped standard errors (based on 1,000 replications) are in parentheses. To contextualize the MEs' magnitudes, the "Propensity to run" row reports the fraction of withdrawals exceeding 75% among all intended withdrawals by finance professionals and differences in such fractions between indicated subject groups. ***, **, and * denote significance at the 1%, 5%, and 10% levels respectively.

Explanatory variable	(1) *Baseline:* Finance pros.	(2) *Increment:* Non-finance pros. – finance pros.	(3) *Increment:* Students – finance pros.	(4) *Increment:* Students – non-finance pros.
Deposit size (in \$100K)	−0.038*	0.006	0.061*	0.054
	(0.02)	(0.03)	(0.04)	(0.04)
Fraction at risk	0.122	0.377	−0.078	−0.455
	(0.26)	(0.42)	(0.46)	(0.51)
Insurance fund	−0.206***	−0.110	0.054	0.164
	(0.04)	(0.09)	(0.09)	(0.10)
Low bank capital	−0.000	0.170	0.035	−0.135
	(0.06)	(0.11)	(0.12)	(0.13)
Fraction at risk × Low bank capital	1.886***	−0.577	−0.472	0.104
	(0.32)	(0.59)	(0.72)	(0.81)
Residual from r_{ij} equation	0.200***	0.001	−0.084	−0.085
	(0.04)	(0.07)	(0.07)	(0.07)
Propensity to run	0.225	−0.008	0.043**	0.051***
H_0: All explanatory variable coefficients are jointly non-significant			χ^2-statistic = 466.52 (*p*-value = 0.000)	
Pseudo R^2			0.2638	

Figure 1: Average Expected Interest Rate Change and Intended Withdrawal Percentage by Account Profile and Subject Group



Appendix

Table A.1: Interest Rate Change Equation with Subject Fixed Effects

This table reports the results of estimating an expected interest rate change equation with subject fixed effects. All estimates pertain to equation (1), which allows for the effects of explanatory variables to vary by depositor type. Column (1) lists coefficients comprising vector α_0, each of which represents the average percentage point change in the interest rate expected by finance professionals following a 1-unit increase in a corresponding explanatory variable. Column (2) presents coefficients on the interactions between the explanatory variables and indicator for a non-finance professional (i.e., coefficient vector α_N); they show the difference in effect magnitudes between non-finance and finance professionals. Column (3) lists coefficients on the interactions between the explanatory variables and indicator for a graduate student (i.e., coefficient vector α_S); they show the difference in the effect magnitudes between students and finance professionals. Column (4) provides the calculated difference in the effect magnitudes between students and non-finance professionals, as implied by the coefficients in columns (3) and (2). The estimation employs a linear panel data regression and uses 4,347 completed interest rate change answers from 551 subjects. Bootstrapped standard errors (based on 1,000 replications) are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels respectively.

Explanatory variable	(1) *Baseline:* Finance pros.	(2) *Increment:* Non-finance pros. – finance pros.	(3) *Increment:* Students – finance pros.	(4) *Increment:* Students – non-finance pros.
Deposit size (in \$100K)	0.011	0.022	−0.021	−0.042
	(0.02)	(0.03)	(0.04)	(0.05)
Fraction at risk	0.076	−0.106	−0.405	−0.298
	(0.17)	(0.31)	(0.47)	(0.51)
Insurance fund	−0.240***	0.026	0.159	0.133
	(0.03)	(0.06)	(0.10)	(0.11)
Low bank capital	0.025	0.174*	0.064	−0.109
	(0.05)	(0.10)	(0.15)	(0.17)
Fraction at risk × Low bank capital	1.159***	−0.184	0.646	0.830
	(0.23)	(0.46)	(0.66)	(0.73)
H_0: All explanatory variable coefficients are jointly non-significant			F-statistic = 18.19	
			(p-value = 0.000)	
H_0: All fixed effects are jointly non-significant			F-statistic = 16.30	
			(p-value = 0.000)	
R^2-within (R^2-overall)			0.0673 (0.0232)	