HOW DOES DEPOSIT INSURANCE AFFECT DEPOSITOR BEHAVIOR IN A BANKING CRISIS?

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Abstract

We use a conjoint analysis-based approach to shed light on depositor behavior in a banking crisis. A multinational sample of respondents is provided with hypothetical account profiles and asked how, following the failure of a large competing bank, they would view each profile in terms of required interest rate premium and deposit withdrawal percentage. Respondents from countries without explicit deposit insurance behave differently. In particular, they exhibit greater withdrawal risk, suggesting that the introduction of deposit insurance during a crisis may be only partially successful in preventing bank runs. They also impose a higher deposit interest rate premium. Having a long-term bank relationship reduces withdrawal risk, as does the absence of co-insurance.

Keywords: deposit insurance, banking crises, bank runs, conjoint analysis

JEL classification: G01, G21

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1. Introduction

The theoretical advantages and disadvantages of deposit insurance are well known. On the one hand, it provides depositors with confidence about the safety of their funds and hence reduces the likelihood of bank runs following an adverse event. On the other hand, it encourages depositors to scale back on their monitoring of bank risk-taking activities during non-crisis periods, thus making future bank failures more likely. In line with the first argument, Demirgüç-Kunt et al. (2014) point out that countries with explicit deposit insurance schemes in place prior to the 2007–08 global financial crisis saw very few depositor-led bank runs, but a widespread incidence of runs on (uninsured) wholesale funding. At the same time, they also express disquiet about the long-term moral hazard implications of this success.[1]

Most empirical research on deposit insurance has focused on existing insurance schemes, either by comparing insured and uninsured countries, or by comparing insured and uninsured depositors within the same country. By contrast, deposit insurance that is introduced during a crisis appears to have attracted little research interest to date. It is, nevertheless, interesting for two reasons. First, from a historical perspective, Demirgüç-Kunt et al. (2008) find that explicit deposit insurance schemes tend to be adopted during a crisis, possibly because more extreme economic conditions generate the necessary political will. A notable example is the very first deposit insurance scheme, that of the United States, which was introduced in 1933 at the height of the Great Depression; during the recent financial crisis, Australia, Singapore and New Zealand all adopted deposit insurance schemes for the first time (although the New Zealand scheme was subsequently withdrawn once the crisis had receded). A natural question is whether such

[1] The evidence of Karas et al. (2013), that traditional measures of depositor-imposed discipline fell sharply after the 2004 introduction of deposit insurance in Russia, suggests this unease may be well-founded.

interventions work in the desired manner.

Second, Demirgüç-Kunt et al. (2014) report that, as of the end of 2013, 77 of the 189 countries they survey do not have explicit deposit insurance schemes. These countries hold a policy option of introducing deposit insurance if and only if a banking crisis of sufficient severity strikes. Such an option could be valuable because it potentially yields the benefits of deposit insurance (lower likelihood of runs on healthy banks) while postponing incurrence of the moral hazard costs. Even if depositors fully anticipate such a policy, delaying the introduction of deposit insurance could still constrain bank risk-taking so long as the pre-requisite conditions for the triggering of deposit insurance require a potentially systemic bank crisis and not just an idiosyncratic, single bank failure. Setting a high barrier for the introduction of deposit insurance could also allow the option to be retained and exercised more than once.[2]

These considerations suggest that there may be a positive net gain in postponing the introduction of deposit insurance until a crisis strikes. However, this implicitly assumes that newly-introduced deposit insurance is just as effective in preventing bank runs as long-standing insurance. Perhaps it takes time for depositors to learn about, and gain confidence in, explicit deposit insurance schemes. In that case, deposit insurance introduced following the onset of a crisis may be of limited value compared to the pre-existing kind.

In this paper, we investigate the effectiveness of explicit deposit insurance that is introduced when banking sector problems arise. The gold standard for doing so would, of course, involve comparing the actual crisis experiences of countries that had a pre-existing deposit insurance system with those that introduced deposit insurance only once the crisis was underway. Unfortunately, because these countries also differ along a multitude of other dimensions (e.g., deposit insurance systems with widely varying features; different forms of crisis, and so on),

[2] As New Zealand appears to be attempting precisely this approach, its long-run experience should be instructive.

implementation of this approach would be a daunting task. Instead, we employ conjoint analysis and ask a sample of respondents to assess a number of hypothetical deposit accounts, all of which are insured to varying degree, in the presence of a banking sector crisis. Because our sample includes respondents both from (i) countries that have explicit deposit insurance and (ii) from countries do not have such insurance, we are able to use the collected responses to gain insight into the potential effectiveness of crisis-adopted deposit insurance.

Our main finding is that respondents from countries without explicit deposit insurance behave differently. In particular, they exhibit greater withdrawal risk, suggesting that the introduction of deposit insurance during a crisis may be only partially successful in preventing bank runs. More generous insurance schemes are more effective but this likely comes at a cost of greater long-term moral hazard risk. Newly-insured respondents also require a higher interest rate premium than their historically-insured counterparts, although there is no difference between the two groups in their pricing of bank risk (as measured by capital buffers).

These results add to, and provide a unique perspective on, recent research on the role of deposit insurance in a banking sector crisis. Madiès (2006), Schotter and Yorulmazer (2009), Iyer and Puri (2012), and Kiss et al. (2012) all find, using various methods, that less generous deposit insurance is less effective at reducing excess deposit withdrawals following a banking sector shock; our results indicate that even newly-insured depositors are similarly able to distinguish between schemes of varying generosity. In the paper that is perhaps most similar in spirit to ours, Karas et al. (2013) compare the reactions of newly-insured and uninsured depositors to a 2004 minor panic in the Russian banking sector; in a related manner, our study attempts to compare the reactions of newly-insured and historically-insured depositors to a hypothetical crisis.

The next section describes our research design in more detail and provides some preliminary (descriptive) analysis of our data. Section 3 outlines our econometric model and its estimation, while section 4 contains the main results. Section 5 discusses some limitations of our study and suggests several interesting directions for future research. Additional technical details appear in an appendix.

2. Research Design and Data Collection

Our analytical approach is straightforward. First, we use conjoint analysis to collect data on depositor responses to a hypothetical bank crisis. Second, we investigate whether these responses are systematically related to deposit insurance features and respondent characteristics.

As described by Louviere (1988), conjoint analysis requires respondents to make judgments about criterion variables based on a series of hypothetical profiles with varying attributes, thus enabling the underlying structure of their cognitive mental models to be statistically inferred from, for example, regression models. In our case, the hypothetical profiles are bank deposit accounts and the attributes describe bank and deposit risk, and features of the deposit insurance system.

This approach is similar to an experimental design, insofar as the situations presented to respondents are hypothetical, and has several advantages over a traditional survey. First, it is less susceptible to "social desirability" and "retrospection" biases: because the situations are hypothetical, respondents need not be swayed by the possible social consequences of their crisis-induced behavior or suffer from recall difficulties. Second, it allows us to investigate how depositors trade off different deposit insurance features of our choosing. For example, a survey would allow us to ask only what actions depositors took during the crisis *given* the deposit insurance system in place at that time. By contrast, our approach allows us to ask what actions they would have taken given different insurance scenarios.

2.1. Deposit account profiles and attributes

Based on work by Garcia (2000), Demirgüç-Kunt and Huizinga (2004), Iyer and Puri (2012), Kiss et al. (2012), Iyer at al. (2013), and Karas et al. (2013), we assign seven attributes to each hypothetical account profile: maximum deposit insurance coverage per deposit ($250,000 or $50,000), deposit size (above or below the maximum deposit insurance coverage), co-insurance provision (100% or 75% guarantee), bank capital buffer level (above or below average), pre-funding of deposit insurance (yes or no), deposit insurance premium type (risk-adjusted or flat), and insurance fund membership by banks (compulsory or voluntary).

We choose two-level manipulations for the attributes, rather than a more complex approach with three or five levels or with continuous values, primarily to keep the survey instrument at a reasonable length and also to minimize the cognitive burden (on respondents) of having to simultaneously evaluate multiple deposit insurance characteristics in each account profile. Nevertheless, the number of possible profile combinations (2^7 = 128) remains infeasibly large, so we use a fractional-factorial design to reduce the number of conjoint profiles to a more manageable number (8).[3] These eight account profiles appear in Table 1.

[Insert Table 1 about here]

To assess the face validity and clarity of the definitions and the instrument, a base conjoint profile and its attributes were extensively pre-tested on a group of depositors and academic faculty. Feedback from this group was used to refine the wording, profiles, and

[3] This design assumes that each attribute is independent of every other predictor. The upside to doing so is that the potentially large number of profiles for each respondent to evaluate is significantly reduced. The downside is that we cannot assess interactions among the attributes. We implement the approach using the fractional-factorial design algorithm in the SPSS conjoint module.

attributes ultimately presented to our respondent sample. Figure 1 summarizes this process and subsequent data collection, which we now explain in more detail.

[Insert Figure 1 about here]

2.2. Respondent sample and data collection

Our sample of respondents consists of 349 business school students at universities in Europe (132 students), New Zealand (122), and the United States (95). There are always pros and cons associated with the use of student respondents, and our study is no exception. On the one hand, focusing on students allows us to more easily construct a multi-national sample containing respondents both from countries with explicit deposit insurance and from countries without such insurance. In addition, business students are likely to have a relatively good understanding of risk-return trade-offs. On the other hand, most students are younger and poorer, have more limited life experience, and are less likely to have experienced a crisis first-hand than the typical depositor. For these reasons, some caution must be applied when trying to generalize from our student sample to the depositor population.

Another important issue for policy conclusions is the extent to which our student respondents are likely to have had a relatively good understanding of deposit insurance; without such an understanding, their answers may be nothing more than guesswork and hence of little value.[4] To address this issue, we re-sampled the same student populations (since the original respondents would have become aware of deposit insurance via their previous participation) to obtain information about their knowledge of deposit insurance. These new samples were presented with a simple hypothetical situation together with a question that required them to

[4] We thank the referee for drawing our attention to this point.

understand fundamental deposit insurance principles. Ninety-one percent of those surveyed answered the question correctly, with no discernible difference between students from countries with explicit deposit insurance and those from countries without it. This result is reassuring on two fronts. First, from the perspective of our study, we can be reasonably confident that our respondent sample was familiar with the concept of deposit insurance. Second, more generally, the high, and homogeneous, awareness of deposit insurance suggests that most countries have, directly or indirectly, been fairly successful in educating depositors about fundamental deposit insurance principles, and that such awareness need not require firsthand experience of a banking crisis.

Our data collection commenced with respondents being told that one of the two largest banks in their country had just failed, and that they would be asked to consider the implications of this event for interest-bearing deposit accounts at their own bank. In order to ensure that they had a common information base, and to keep the number of variables used in the subsequent analysis at a manageable level, all respondents were instructed:

(i) that the term “bank” refers to any depository institution covered under the country’s deposit insurance system, and that each deposit account is at least partially covered by deposit insurance;

(ii) that while their bank’s assets were diversified, the bank itself was not considered “too big to fail;”

(iii) that their bank had no additional debt obligations, or preferred shares, which would have priority over common shares in the case of bank liquidation (and so may encourage additional monitoring);

(iv) that their bank was 100% owned by the domestic private sector;

(v) to assume that they did not have any deposits at other banks (to rule out possible interbank complications);

(vi) that any failed bank would be closed promptly (so as to minimize transaction costs associated with any form of forbearance);

(vii) that the country's deposit insurance agency could not fail.[5]

Respondents also reported several personal characteristics: gender, whether they had had an actual bank account for five years or more, whether they opened this account following advice from another customer, and whether they had other bank relationships (such as a loan) in addition to this account. Most importantly, they were asked to identify their home country. Our respondents originate from a wide range of countries: Austria, China, Egypt, Finland, Germany, Hungary, Italy, Liechtenstein, Malaysia, New Zealand, Philippines, Russia, Slovakia, South Korea, Sri-Lanka, Switzerland, Taiwan, United Kingdom, and USA. Crucially, three countries on the list—China, Egypt, and New Zealand—do not have explicit deposit insurance schemes. This feature of the data allows us to compare the reaction to a bank failure of respondents originating from countries without explicit deposit insurance to that of respondents from countries with such insurance.

Respondents were also asked to assess two statements designed to elicit information about their risk preferences:

Risk Tradeoff Statement: "I am willing to take high financial risks in order to realize higher average yields;"

Risk Tolerance Statement: "I usually view myself as a risk taker."

Responses indicated the degree of agreement (or disagreement) with these statements, based on a seven-point Likert scale ranging from "strongly disagree" (1) to "strongly agree" (7). Although the sample correlation between the responses to these two statements is strongly positive (0.61;

[5] In practice, depositors have not always had this luxury. In section 4, we discuss this issue in more detail and explore potential implications of allowing for possible insolvency of the deposit insurance provider.

std. error = 0.03), it is also significantly less than one, suggesting that the two statements capture different aspects of risk preferences.

Table 2 presents the definitions of the account and respondent characteristics, and the terminology used to identify them throughout the remainder of this paper. For the two risk preference statements, we anticipate our subsequent regression analysis and combine the "strongly disagree" and "disagree" responses into one category; we do the same for the "strongly agree" and "agree" responses.

[Insert Table 2 about here]

Table 3 provides selected summary statistics for the respondent variables. Sixty-one percent of respondents are male, 66% have had an actual bank account for at least five years, 45% have at least two other relationships with the bank besides that account, and 28% opened that account on the advice of another customer. The risk preference statements reveal an interesting asymmetry: the frequency of risk tolerance responses declines monotonically with the level of agreement (i.e., respondents tend not to see themselves as risk takers), but the frequency of risk tradeoff responses is more heavily weighted towards the agreement end of the Likert scale (i.e., respondents are prepared to take risks that yield higher returns).

We also compare characteristics of two subsamples–respondents originating from countries that have explicit deposit insurance and those from countries that do not. Respondents in the latter group are significantly less likely to have had an actual bank account for five or more years and to have multiple bank relationships, but are more likely to have opened the account on another customer's advice. However, Table 3 reveals little evidence of any difference in risk preferences, both individually and jointly. To more rigorously assess this latter point, we undertake a Pearson χ^2 test of response distribution independence; under the null hypothesis of independence, the test statistic is distributed as a $\chi^2(4)$.[6] For the risk tradeoff statement, the test statistic value is 3.30 and the p-value is 0.51; for the risk tolerance statement, the statistic is 5.97 and p-value is 0.20. Thus, the distribution of respondent risk preferences in our sample appears to be unaffected by prior exposure to deposit insurance.

[Insert Table 3 about here]

2.3. Preliminary analysis

For each account profile, respondents were asked two questions about their reaction to news of the bank failure:

Question 1: "Compared to competing financial institutions, I would expect an annualized interest rate for this account to be…" The response options are categorical on a nine-point scale, ranging from "significantly lower" (1) to "significantly higher" (9). We chose to seek qualitative (rather than quantitative) answers to this question, partly to reduce the potential for non-response due to respondent fatigue and partly to avoid comparability problems caused by the range of home countries represented in our sample.

Question 2: "On hearing about the news of the shock to the financial system, what percentage of your deposit are you likely to immediately withdraw?" The response options are arranged in 11 steps from 0% to 100%, with a step size of 10%. We chose to restrict the set of possible answers in this way to reduce non-response risk while still covering the entire range of possible withdrawals.

Tables 4 and 5 present the distribution of responses to these two questions, pooled across the eight account profiles. For the full sample, the interest premium responses are largely

[6] Bartoszyński and Niewiadomska-Bugaj (1996, p. 767) provide details on this test.

symmetric around the middle of the response scale while the deposit withdrawal responses are concentrated in the 50% or below range. More interesting are the differences between the respondents whose home countries do and do not have explicit deposit insurance. The latter group is more likely to require a higher interest premium and to withdraw 50% or more of their deposit following the news of a major bank failure. Also, Pearson χ^2 tests strongly reject equality of the response distributions between the respondent groups, suggesting that depositor reactions to a bank failure may depend on prior exposure to deposit insurance.[7]

[Insert Tables 4 and 5 about here]

3. Empirical Model and Estimation Approach

Tables 4 and 5 suggest that depositors with prior exposure to deposit insurance are less likely to respond negatively (i.e., require a higher interest rate or withdraw a significant percentage of their deposit) to news about a major bank failure than those without such exposure. Why might this be the case? One possibility is that different economic experiences affect the views and behavior of economic agents—see Osili and Paulson (2014). It could be, for example, that respondents from countries with explicit deposit insurance have a priori different beliefs, based on different life experiences with depositor protection schemes and banking systems generally, about the safety of bank deposits and the effectiveness of deposit insurance. However, Table 3 shows that such respondents also differ in terms of other factors that could potentially affect the reaction to the bank failure news. For example, they are more likely to have had a long-term relationship with their bank, which could make deposit withdrawal less likely (Iyer and Puri, 2012). Moreover, and importantly, the effect of prior deposit insurance exposure on responses

[7] In un-tabulated results, we assess subsample differences separately for each account profile and find evidence of significant differences for profiles 2, 3, 5, and 7. These results are available on request from the authors.

may itself be influenced by specific deposit insurance features (such as the maximum coverage limit, co-insurance, and other account profile attributes). To disentangle these various effects, we must turn to multivariate regression methods.

Doing so, however, is by no means straightforward. First, the data generated by the two response questions are not numerical. Second, the 16 answers provided by each respondent are unlikely to be independent due to unobservable respondent-specific factors. Third, common unobservable factors are likely to induce correlation between the answers to the interest premium and deposit withdrawal questions. Our econometric approach, described below and in the appendix, aims to address these issues.

To deal with the first issue, we employ a latent variable framework. Let π_{ij} denote the respondent i's answer to the interest premium question for account profile j, where i = 1,2,…,349 and j = 1,2,…,8. We relate this answer to an underlying latent (i.e., unobserved) continuous variable π_{ij}^* as follows (e.g., see Maddala, 1983):

$$\pi_{ij} = k \text{ if and only if } \pi_{ij}^* \in (\mu_k, \mu_{k+1}], \text{ for } k = 1,2,\ldots,9, \tag{1}$$

where $\mu_1 < \mu_2 < \ldots < \mu_{10}$ are "thresholds" on the latent variable scale. Here, μ_1 and μ_{10} are set to $-\infty$ and $+\infty$ respectively, and μ_2 is normalized to zero for identification reasons. The other seven thresholds, μ_3 through μ_9, are estimated.

Similarly, let w_{ij} denote respondent i's answer to the deposit withdrawal question for profile j. We specify that the respondent selects a particular answer category if an underlying latent continuous variable w_{ij}^* falls within a ±5% interval centered at the percentage defining the category. For example, w_{ij} is "30%" if w_{ij}^* is between 25 and 35 (%). More formally:

$$w_{ij} = l \text{ if and only if } w_{ij}^* \in (\nu_l, \nu_{l+1}], \text{ for } l = 1,2,\ldots,11, \tag{2}$$

where the "thresholds" $\nu_1 = -\infty, \nu_l = 10 \cdot (l - 1) - 5$ for $l = 2,3,\ldots,11$, and $\nu_{12} = +\infty$. Eq. (2)

differs from Eq. (1) in that all thresholds, ν_1 through ν_{12}, are set to specific values rather than estimated. Note that the latent variable w_{ij}^* can be interpreted as the actual percentage of the deposit to be withdrawn (i.e., unlike the recorded response w_{ij}, the unobserved w_{ij}^* is not restricted to be an integer multiple of 10%).

With the dependent variables defined in this way, we specify and estimate the following system of equations:

$$\pi_{ij}^* = \theta_\pi \cdot D_i + \boldsymbol{p}_j' \cdot \boldsymbol{\alpha}_\pi + D_i \cdot \boldsymbol{p}_j' \cdot \boldsymbol{\beta}_\pi + \boldsymbol{z}_{Ai}' \cdot \boldsymbol{\gamma}_\pi + \boldsymbol{x}_i' \cdot \boldsymbol{\kappa}_\pi + \lambda_{\pi i} + \epsilon_{\pi ij}, \tag{3}$$

$$w_{ij}^* = \theta_w \cdot D_i + \boldsymbol{p}_j' \cdot \boldsymbol{\alpha}_w + D_i \cdot \boldsymbol{p}_j' \cdot \boldsymbol{\beta}_w + \boldsymbol{z}_{Bi}' \cdot \boldsymbol{\gamma}_w + \boldsymbol{x}_i' \cdot \boldsymbol{\kappa}_w + \pi_{ij}^* \cdot \delta_{wi} + \lambda_{wi} + \epsilon_{wij}, \tag{4}$$

where $D_i = 1$ if and only if respondent i's home country does not have explicit deposit insurance, $\boldsymbol{p}_j$ is the vector of dummy variables representing account profile attributes, $\boldsymbol{z}_{Ai}$ is the vector of dummy variables representing the response to the risk tradeoff statement, $\boldsymbol{z}_{Bi}$ is the vector of dummy variables representing the response to the risk tolerance statement, and $\boldsymbol{x}_i$ is the vector of the remaining respondent-characteristic variables appearing in Table 2. The terms $\lambda_{\pi i}$ and λ_{wi} account for unobservable respondent-specific factors that do not vary across the eight account profiles. Such factors may include respondent views regarding interest rates (i.e., reflecting inter-temporal consumption substitution), respondent interpretation of the deposit withdrawal question, and so on. Because $\lambda_{\pi i}$ and λ_{wi} imply dependence of the unobserved determinants of respondent i's answers across the eight account profiles, we estimate our econometric model by maximum likelihood, while expressing the likelihood contribution of a respondent as the joint probability of all his/her interest premium and deposit withdrawal answers (there are 16 such answers in total per respondent).[8]

As the error terms $\epsilon_{\pi ij}$ and ϵ_{wij} may be driven by the same unobserved respondent- and profile-specific factors (e.g., perceptions of respondent i regarding the description of profile j),

[8] The likelihood contribution formula is derived in the appendix.

we allow these error terms to be mutually correlated in the joint estimation of Eqs. (3) and (4).[9] We include π_{ij}^{*} on the right hand side of Eq. (4) due to possible feedback between a respondent's choice of interest premium and withdrawal rate. For example, the withdrawal rate for a particular account profile may be low if the respondent has indicated a high expected interest premium. We also allow this feedback effect to vary depending on whether or not the respondent originated from a country with explicit deposit insurance:

$$\delta_{wi} = \delta_w + \Delta_w \cdot D_i. \tag{5}$$

The underlying intuition of the system modeled by Eqs. (3) and (4) is straightforward. Upon learning about a major bank failure, and hence of the potential for a banking sector crisis, a respondent first decides on the interest premium required on his deposit (Eq. (3)). Then, taking this interest premium into account, he chooses how much of the deposit to withdraw (Eq. (4)). While conceptually necessary, the inclusion of π_{ij}^{*} in Eq. (4) creates a potential endogeneity problem. To obtain consistent parameter estimates, we follow the conventional "exclusion restriction" approach outlined by Greene (2012, Ch. 10) for systems of simultaneous equations.[10] This approach requires an explanatory variable that affects π_{ij}^{*}, but has no direct impact on the conditional expectation of w_{ij}^{*} given π_{ij}^{*} and other explanatory variables from Eq. (4).

We adopt an exclusion restriction based on responses to the risk preference statements. Recall that the first of these statements (*"I am willing to take high financial risks in order to realize higher average yields")* asks respondents about their willingness to trade off risk and return while the second (*"I usually view myself as a risk taker"*) asks about their willingness to tolerate risk in general. Although the two statements obviously pick up similar respondent characteristics, the first has most direct relevance for interest premium setting while the second is

[9] Subsequent estimation results indicate that this correlation is positive and statistically significant. For the specific distributional assumptions imposed on the ϵ and λ terms, see the appendix.
[10] See Maddala and Lee (1976) for a discussion of the latent variable case.

more closely linked to withdrawal risk. Thus, once the direct effects of the interest premium (π_{ij}^*) and risk tolerance ($\boldsymbol{z}_{Bi}$) on withdrawal (w_{ij}^*) are accounted for, it seems reasonable to assume that risk tradeoff propensity ($\boldsymbol{z}_{Ai}$) provides no additional information about withdrawal risk.[11] That is, $\boldsymbol{z}_{Ai}$ serves as a vector of instruments for π_{ij}^* and hence satisfies the exclusion restriction. Moreover, because $\boldsymbol{z}_{Ai}$ contains multiple variables, the system of Eqs. (3)–(4) is over-identified. In section 4, we use this property to perform diagnostic Lagrange multiplier (LM) tests of the restriction as suggested by Hausman (1983).[12]

The coefficients θ_π, $\boldsymbol{\alpha}_\pi$, $\boldsymbol{\beta}_\pi$, $\boldsymbol{\gamma}_\pi$, and $\boldsymbol{\kappa}_\pi$ in Eq. (3) are specified on the latent variable scale, so their estimates can only be interpreted qualitatively. By contrast, the estimates of $\theta_w, \delta_w, \Delta_w, \boldsymbol{\alpha}_w, \boldsymbol{\beta}_w, \boldsymbol{\gamma}_w$, and $\boldsymbol{\kappa}_w$ in Eq. (4) may be interpreted quantitatively: they measure numerical changes in the percentage of deposit to be withdrawn. Of particular interest are the estimates of $\theta_\pi, \theta_w, \boldsymbol{\beta}_\pi$, and $\boldsymbol{\beta}_w$ as these reflect differences in responses attributable to variation in prior exposure to deposit insurance. Recall that we distinguish between respondents whose home country offers explicit deposit insurance and those whose home country provides no such protection. Since all our hypothetical account profiles offer deposit insurance, we can think of the two respondent groups as representing "historically-insured" and "newly-insured" depositors respectively. Thus, the estimates of $\theta_\pi, \theta_w, \boldsymbol{\beta}_\pi$, and $\boldsymbol{\beta}_w$ can shed light on the effectiveness of introducing deposit insurance during a crisis.

4. Regression Model Results

The results from estimating the system of Eqs. (3) and (4) appear in Table 6. From a policy perspective, our primary interest is in the extent to which deposit insurance helps mitigate

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[11] More formally, we assume that w_{ij}^* is conditionally mean-independent of $\boldsymbol{z}_{Ai}$; see Manski and Pepper (2000, p. 998).

[12] Note that we also exclude $\boldsymbol{z}_{Bi}$ from Eq. (3), but this exclusion is not critical for identification of the model; it is supported by specification test results (for details, see section 4).

withdrawal risk. Regardless of respondent background, deposit insurance seems to matter: deposits with an uninsured component ("large deposits," i.e., those above the coverage limit) require a significantly higher interest rate and have an excess withdrawal rate of more than 20 percentage points.[13] However, the overall effectiveness of deposit insurance in mitigating withdrawal risk depends on respondents' prior exposure to deposit insurance. From the first row of Table 6, we see that the average small deposit withdrawal rate is 33.62 percentage points greater among newly-insured respondents than it is among historically-insured respondents, a difference that is statistically significant at the 1% level. For large deposits, the difference is 24.72 (= 33.62 – 8.90) percentage points. These results suggest that the introduction of deposit insurance during a crisis may be less successful than an already-existing insurance scheme in mitigating withdrawal risk.

[Insert Table 6 about here]

Nevertheless, certain deposit insurance features can close this gap considerably. In particular, the difference in withdrawal rate between newly- and historically-insured respondents falls by 18.6 percentage points if the deposit insurance scheme covers 100% (rather than 75%) of eligible deposit amounts, an estimate that differs from zero at the 1% significance level. This estimate suggests that any deposit insurance scheme introduced during a crisis must be transparently generous in order to have the desired impact on withdrawal risk. This result is similar to, but distinct from, those of Madiès (2006) and Schotter and Yorulmazer (2009), who find that existing deposit insurance systems are more effective at preventing bank runs when they require little or no co-insurance.

[13] From the third column of Table 6, the estimated withdrawal rate for large deposits is 31.66% among historically-insured respondents and (31.66-8.90) = 22.76% among newly-insured respondents.

Although our research design precludes detailed investigation, it seems likely that this finding on insurance scheme generosity is at least partially neutralized by imperfect credibility of the insurance promise. Recall that we instruct respondents to assume that the deposit insurance provider cannot fail. Such an assumption has not always been borne out in practice—for example, the Iceland government's default on insurance payments to foreign depositors of *Landsbanki* in 2008. Similarly, Ennis and Keister (2009) argue that bank runs in Argentina in 2001 were partly attributable to depositor fears about the credibility of the government's insurance scheme. Moreover, Martinez Peria and Schmukler (2001) discuss several cases where market discipline was unaffected by the presence of deposit insurance, an outcome they attribute to depositor doubts about the solvency of the provider. Allowing for imperfect credibility would thus appear likely to affect depositor behavior in a similar manner to co-insurance.

A pre-funded deposit insurance scheme lowers the difference by a further 9.87 points (significant at the 5% level), a finding that is somewhat more difficult to interpret given that pre-funding is unlikely to have any impact on the short-run attractiveness of a newly-introduced scheme. Nevertheless, it may reflect a belief among newly-insured respondents that holdup problems are less likely with such a provision. For example, an insurance scheme that is rushed into existence during a crisis may not seem particularly convincing to depositors who worry that unforeseen complications could result in payout delays. In these circumstances, the existence of a pre-funding provision could signal to depositors that banking administrators have devoted sufficient thought to the details of the new insurance scheme.

Although less serious than bank runs in the short-term, excessive deposit interest rate increases have the potential to raise banks' funding costs, with a consequent adverse effect on investment and general economic activity. Table 6 shows that newly-insured respondents tend to require a significantly higher interest premium than their historically-insured counterparts (coefficient estimate = 0.73; *p*-value < 0.01), which suggests that introducing deposit insurance during a crisis may be relatively ineffective in moderating funding risk. However, this difference is smaller for schemes with no co-insurance (coefficient estimate = -0.33; *p*-value = 0.03). Also, despite requiring a higher interest premium in general, newly-insured respondents reveal no greater tendency towards risk-pricing than do historically-insured respondents: the estimated sensitivity of the interest premium to bank capital is statistically indistinguishable between the two groups (coefficient estimate = -0.01; *p*-value = 0.94).

To the extent that funding risk may be seen as less harmful than withdrawal risk, another policy question of interest is the extent to which depositors can be encouraged to respond to a crisis by requiring higher interest rates rather than withdrawing deposits. The estimates in Table 6 suggest there may be some scope for such response: respondents who most strongly agree with the risk tradeoff statement require a relatively large interest premium, but the closely-related respondents who most strongly agree with the risk tolerance statement withdraw relatively less of their deposit. Although the latter effect is economically fairly small (4.85 percentage points), it is statistically significant at the 1% level.

The respondent background characteristics (other than prior exposure to deposit insurance) do not tend to affect the required interest premium or withdrawal rate. The one exception is the length of an existing bank relationship: respondents who have held an actual bank account for more than five years withdraw less, but also require a higher interest premium, than others. More familiarity with banking, it seems, breeds respect (in the sense of smaller withdrawals), but also some caution.[14]

[14] Using depositor data from an Indian bank that experienced a run following the failure of a neighboring bank, Iyer and Puri (2012) document a similar effect.

4.1. Specification and goodness-of-fit tests

To check our empirical specification, we perform several post-estimation tests. First, recall that responses to the risk tolerance statement are not included among the explanatory variables in the deposit withdrawal equation, i.e., the vector $\boldsymbol{z}_{Ai}$ does not appear on the right hand side of Eq. (4). If the exclusion were invalid, the model would be misspecified and our estimates would be inconsistent. As discussed in section 3, this exclusion restriction is a source of identification, and we can exploit the over-identification property to implement diagnostic testing by using the Lagrange multiplier (LM) test suggested by Hausman (1983). Under the null hypothesis of this test, the true coefficient on $\boldsymbol{z}_{Ai}$ in Eq. (4) is zero. We perform several LM tests corresponding to different subsets of the variables in $\boldsymbol{z}_{Ai}$, and the resulting *p*-values range from 0.24 to 0.91. Thus, the null hypothesis is not rejected.[15]

Second, recall also that responses to the risk tradeoff statement are not included among the explanatory variables in the interest premium equation, i.e., the vector $\boldsymbol{z}_{Bi}$ does not appear on the right hand side of Eq. (3). The general approach here is analogous to that for testing the exclusion of $\boldsymbol{z}_{Ai}$, except that only one LM test is now required.[16] We compute a test statistic value of 3.82 with a p-value of 0.43. Hence, the null is not rejected at conventional significance levels, which provides further support for the chosen model specification.

In summary, even though these post-estimation tests are purely diagnostic, and as such cannot provide definitive proof of the validity of the imposed restrictions, the results obtained are consistent with our chosen empirical specification.

Finally, to formally assess the in-sample goodness-of-fit of our model, we compare actual

[15] If the entire vector $\boldsymbol{z}_{Ai}$ were included in Eq. (4), the model would be unidentified and an LM test could not be implemented (Hausman, 1983). Thus, we test for the validity of excluding a proper subset of the variables comprising $\boldsymbol{z}_{Ai}$. Since there are several such subsets, this testing procedure requires us to perform several LM tests. Given the inherent limitations of such a procedure, evidence from this testing should be taken as suggestive only.

[16] Note that our model would still be identified even if the entire vector $\boldsymbol{z}_{Bi}$ were included in Eq. (3).

and predicted distributions of responses for three threshold withdrawal percentages: 10%, 20%, and 30%. That is, for each threshold, we calculate the proportion of respondents who our model predicts will choose to withdraw less than that amount and then compare it to the proportion of respondents who actually say they will withdraw less than this amount. Differences between the two are tested for statistical significance using χ^2 tests (see Bartoszyński and Niewiadomska-Bugaj, 1996, p. 758).

The results of this exercise appear in Table 7. For the full sample, and for the newly-insured and historically-insured subsamples, the actual and the predicted distributions are very similar; in no case are we able to reject the null hypothesis of a good model fit to the data. These results also reinforce our earlier finding of higher withdrawal rates among the newly-insured group of respondents.

[Insert Table 7 about here]

5. Concluding Remarks

When a banking crisis strikes, can the belated introduction of deposit insurance help prevent bank runs? Our results suggest that such a policy response may only be partially successful, at least compared to the effectiveness of a pre-existing insurance scheme. Faced with a hypothetical bank failure, respondents from countries without deposit insurance indicate they would withdraw a greater percentage from insured accounts, and require a higher interest premium on these accounts, than respondents from countries with explicit deposit insurance. To some extent at least, more generous insurance schemes are more effective at reducing these excess withdrawal and funding risks.

These results have intriguing and policy-relevant implications. Nevertheless, some caution is advisable as our study has several limitations that should be kept in mind. First, in common with experimental-type research, our data are obtained from hypothetical situations. Actual depositors, faced with sharper incentives, may behave differently. This concern is potentially exacerbated by our use of student respondents: the combination of weak incentives and generally lower wealth, for example, may cause our respondents' reported risk attitudes to differ from those of the depositor population, which could skew the impact of deposit insurance. Second, our analytical approach necessarily simplifies the choices faced by real-world depositors. To make the analysis tractable, we consider only a subset of possible deposit insurance attributes, and limited variation in these attributes. Actual insurance systems vary much more markedly, and may affect depositor behavior in ways that our analysis cannot identify.

Finally, our study leaves some interesting questions for future research. While we focus on the immediate reaction of depositors to news about a major bank failure, and hence on the short-run effectiveness of deposit insurance, an obviously important policy issue concerns the potential implications of a new, crisis-adopted insurance scheme for long-run moral hazard risk. Does the extent of depositor monitoring in such a case quickly converge to that prevailing in countries with long-established insurance schemes, or might there be a persistent "crisis dividend?" Moreover, as implied by the work of Nier and Baumann (2006), does the speed of such convergence depend on the level of bank competition and the generosity of the newly-introduced insurance scheme? In addition, because our research design requires each respondent to answer questions in isolation from other respondents, it does not allow for social network effects (see Iyer and Puri, 2012; Kiss et al., 2014). To the extent that such effects can influence the ability of depositors to distinguish between fundamental shocks and panics, they may have important implications for the relative effectiveness of crisis-adopted deposit insurance.

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Appendix

This appendix outlines assumptions imposed on the unobserved components of the econometric model (see section 3) and derives the likelihood contribution formula. To begin, we do two things. First, to avoid notational overload, we collect several explanatory variables into a single vector $\boldsymbol{q}_{ij} = \left[D_i, \boldsymbol{p}'_j, D_i \cdot \boldsymbol{p}'_j\right]$, define coefficient vectors $\widetilde{\boldsymbol{\alpha}}_\pi = [\theta_\pi, \boldsymbol{\alpha}'_\pi, \boldsymbol{\beta}'_\pi]'$ and $\widetilde{\boldsymbol{\alpha}}_w = [\theta_w, \boldsymbol{\alpha}'_w, \boldsymbol{\beta}'_w]'$, and rewrite Eqs. (3) and (4) as:

$$\pi^*_{ij} = \boldsymbol{q}'_{ij} \cdot \widetilde{\boldsymbol{\alpha}}_\pi + \boldsymbol{z}'_{Ai} \cdot \boldsymbol{\gamma}_\pi + \boldsymbol{x}'_i \cdot \boldsymbol{\kappa}_\pi + \lambda_{\pi i} + \epsilon_{\pi ij}, \tag{3'}$$

$$w^*_{ij} = \boldsymbol{q}'_{ij} \cdot \widetilde{\boldsymbol{\alpha}}_w + \boldsymbol{z}'_{Bi} \cdot \boldsymbol{\gamma}_w + \boldsymbol{x}'_i \cdot \boldsymbol{\kappa}_w + \pi^*_{ij} \cdot \delta_{wi} + \lambda_{wi} + \epsilon_{wij}. \tag{4'}$$

Second, we specify that the error-term vector $(\epsilon_{\pi ij}, \epsilon_{wij})'$ is conditionally independent and identically distributed (i.i.d.) across i and j as a normal random vector:

$$\begin{pmatrix} \epsilon_{\pi ij} \\ \epsilon_{wij} \end{pmatrix} | \lambda_{\pi i}, \lambda_{wi}, D_i, \boldsymbol{p}_1, \dots, \boldsymbol{p}_8, \boldsymbol{x}_i, \boldsymbol{z}_{Ai}, \boldsymbol{z}_{Bi} \sim i.i.d.\, N\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho_{\pi w}\sigma_w \\ \rho_{\pi w}\sigma_w & \sigma_w^2 \end{pmatrix}\right), \tag{A.1}$$

where $\rho_{\pi w}$ is the correlation coefficient ($|\rho_{\pi w}| < 1$), and $\sigma_w > 0$ is the standard deviation of ϵ_{wij}. The standard deviation of $\epsilon_{\pi ij}$ is normalized to one for identification reasons, because the interest premium responses are ordered categorical (see Maddala, 1983). In contrast, since the deposit withdrawal responses are interval-type, the standard deviation of ϵ_{wij}, σ_w, can be estimated.

We substitute Eq. (3′) into Eq. (4′) to obtain a reduced-form system:

$$\pi^*_{ij} = \boldsymbol{q}'_{ij}\widetilde{\boldsymbol{\alpha}}_\pi + \boldsymbol{z}'_{Ai}\boldsymbol{\gamma}_\pi + \boldsymbol{x}'_i\boldsymbol{\kappa}_\pi + \lambda_{\pi i} + u_{\pi ij}, \tag{A.2}$$

$$w^*_{ij} = \boldsymbol{q}'_{ij}(\widetilde{\boldsymbol{\alpha}}_w + \widetilde{\boldsymbol{\alpha}}_\pi\delta_{wi}) + \boldsymbol{z}'_{Ai}\boldsymbol{\gamma}_\pi\delta_{wi} + \boldsymbol{z}'_{Bi}\boldsymbol{\gamma}_w + \boldsymbol{x}'_i(\boldsymbol{\kappa}_w + \boldsymbol{\kappa}_\pi\delta_{wi}) + \lambda_{wi} + \lambda_{\pi i}\delta_{wi} + u_{wij}, \tag{A.3}$$

where $u_{\pi ij} = \epsilon_{\pi ij}$ and $u_{wij} = \epsilon_{\pi ij}\delta_{wi} + \epsilon_{wij}$. Eq. (A.1) implies that the error-term vector $(u_{\pi ij}, u_{wij})'$ is a normal random vector:

$$\begin{pmatrix} u_{\pi ij} \\ u_{wij} \end{pmatrix} | \lambda_{\pi i}, \lambda_{wi}, D_i, \boldsymbol{p}_1, \dots, \boldsymbol{p}_8, \boldsymbol{x}_i, \boldsymbol{z}_{Ai}, \boldsymbol{z}_{Bi} \sim$$

$$N\left(\begin{pmatrix}0\\0\end{pmatrix},\begin{pmatrix}1 & \delta_{wi}+\rho_{\pi w}\sigma_w\\ \delta_{wi}+\rho_{\pi w}\sigma_w & \delta_{wi}^2+2\rho_{\pi w}\sigma_w\delta_{wi}+\sigma_w^2\end{pmatrix}\right). \tag{A.4}$$

The respondent-specific terms $\lambda_{\pi i}$ and λ_{wi} are modeled as random effects. In particular, we specify that each of the λ's is conditionally i.i.d. across i as a normal random variable:

$$\lambda_{mi}|D_i,\boldsymbol{p}_1,\ldots,\boldsymbol{p}_8,\boldsymbol{x}_i,\boldsymbol{z}_{Ai},\boldsymbol{z}_{Bi}\sim i.i.d.N(0,\omega_m^2), \tag{A.5}$$

where $\omega_m > 0$ is the standard deviation and $m = \pi, w$. We do not estimate the individual λ's, but rather we estimate the standard deviations ω_π and ω_w. Statistically significant estimates of the ω's would indicate the existence of dependence of the unobserved determinants of a respondent's interest premium and deposit withdrawal responses across the eight account profiles. In our model, it is not feasible to specify the individual λ's as fixed effects and estimate them consistently, because the number of parameters to estimate would be increasing in the number of respondents. Also, we do not allow for $\lambda_{\pi i}$ and λ_{wi} to be correlated with each other, since a preliminary analysis showed that such correlation could not be separately identified (however, recall that we allow for the error terms $\epsilon_{\pi ij}$ and ϵ_{wij} to be correlated with each other).

We collect all model parameters to estimate into a vector $\boldsymbol{\Phi}$:

$$\boldsymbol{\Phi}=(\widetilde{\boldsymbol{\alpha}}_\pi',\boldsymbol{\gamma}_\pi',\boldsymbol{\kappa}_\pi',\widetilde{\boldsymbol{\alpha}}_w',\boldsymbol{\gamma}_w',\boldsymbol{\kappa}_w',\delta_w,\Delta_w,\mu_3,\mu_4,\ldots,\mu_9,\sigma_w,\rho_{\pi w},\omega_\pi,\omega_w)'. \tag{A.6}$$

The likelihood contribution of respondent i, denoted as $L_i(\boldsymbol{\Phi})$, is the joint probability of all of the respondent's interest premium and deposit withdrawal responses (there are 16 such responses in total per respondent), conditional on the respondent's prior exposure to deposit insurance, attributes of the eight profiles, and respondent's background characteristics and risk preferences:

$$L_i(\boldsymbol{\Phi})=\Pr[(\pi_{i1},w_{i1}),\ldots,(\pi_{i8},w_{i8})|D_i,\boldsymbol{p}_1,\ldots,\boldsymbol{p}_8,\boldsymbol{x}_i,\boldsymbol{z}_{Ai},\boldsymbol{z}_{Bi};\boldsymbol{\Phi}]. \tag{A.7}$$

Eq. (A.1) implies that conditional on the random effects $\lambda_{\pi i}$ and λ_{wi}, the random vector $(\pi_{ij}^*,w_{ij}^*)'$ is independent across j. Thus, $L_i(\boldsymbol{\Phi})$ in Eq. (A.7) can be expressed as:

$$L_i(\boldsymbol{\Phi})=\iint\Pr[(\pi_{i1},w_{i1}),\ldots,(\pi_{i8},w_{i8})|\lambda_{\pi i},\lambda_{wi},D_i,\boldsymbol{p}_1,\ldots,\boldsymbol{p}_8,\boldsymbol{x}_i,\boldsymbol{z}_{Ai},\boldsymbol{z}_{Bi};\boldsymbol{\Phi}]\times$$

$$dF(\lambda_{\pi i}, \lambda_{wi}|D_i, \boldsymbol{p}_1, \dots, \boldsymbol{p}_8, \boldsymbol{x}_i, \boldsymbol{z}_{Ai}, \boldsymbol{z}_{Bi}; \boldsymbol{\Phi}) =$$

$$\iint \prod_{j=1}^{8} \Pr\left[(\pi_{ij}, w_{ij})\middle|\lambda_{\pi i}, \lambda_{wi}, D_i, \boldsymbol{p}_1, \dots, \boldsymbol{p}_8, \boldsymbol{x}_i, \boldsymbol{z}_{Ai}, \boldsymbol{z}_{Bi}; \boldsymbol{\Phi}\right] \times$$

$$dF(\lambda_{\pi i}, \lambda_{wi}|D_i, \boldsymbol{p}_1, \dots, \boldsymbol{p}_8, \boldsymbol{x}_i, \boldsymbol{z}_{Ai}, \boldsymbol{z}_{Bi}; \boldsymbol{\Phi}), \tag{A.8}$$

where $F(\lambda_{\pi i}, \lambda_{wi}|\cdot)$ is the joint cumulative distribution function of the random effects, as implied by Eq. (A.5). Here, $dF(\lambda_{\pi i}, \lambda_{wi}|\cdot) = \frac{1}{2\pi\omega_\pi\omega_w} \cdot \exp\left(-\frac{1}{2} \cdot \left[\frac{\lambda_{\pi i}^2}{\omega_\pi^2} + \frac{\lambda_{wi}^2}{\omega_w^2}\right]\right) \cdot d\lambda_{\pi i} d\lambda_{wi}$. We evaluate the double integral in Eq. (A.8) numerically by using a quadrature method.

To express the conditional probability $\Pr\left[(\pi_{ij}, w_{ij})\middle|\lambda_{\pi i}, \lambda_{wi}, \cdot\right]$ in Eq. (A.8), we apply the reduced-form Eqs. (A.2) and (A.3) as well as Eqs. (1) and (2) linking π_{ij} to π_{ij}^* and w_{ij} to w_{ij}^*:

$$\Pr\left[(\pi_{ij}, w_{ij})\middle|\lambda_{\pi i}, \lambda_{wi}, \cdot\right] = \Pr[\mu_{\pi_{ij}} < \pi_{ij}^* \le \mu_{\pi_{ij}+1}, \nu_{w_{ij}} < w_{ij}^* \le \nu_{w_{ij}+1}|\lambda_{\pi i}, \lambda_{wi}, \cdot]$$

$$= \Pr[\mu_{\pi_{ij}} < \boldsymbol{q}_{ij}'\widetilde{\boldsymbol{\alpha}}_\pi + \boldsymbol{z}_{Ai}'\boldsymbol{\gamma}_\pi + \boldsymbol{x}_i'\boldsymbol{\kappa}_\pi + \lambda_{\pi i} + u_{\pi ij} \le \mu_{\pi_{ij}+1}, \nu_{w_{ij}} < \boldsymbol{q}_{ij}'(\widetilde{\boldsymbol{\alpha}}_w +$$

$$\widetilde{\boldsymbol{\alpha}}_\pi\delta_{wi}) + \boldsymbol{z}_{Ai}'\boldsymbol{\gamma}_\pi\delta_{wi} + \boldsymbol{z}_{Bi}'\boldsymbol{\gamma}_w + \boldsymbol{x}_i'(\boldsymbol{\kappa}_w + \boldsymbol{\kappa}_\pi\delta_{wi}) + \lambda_{wi} + \lambda_{\pi i}\delta_{wi} + u_{wij} \le$$

$$\nu_{w_{ij}+1}|\lambda_{\pi i}, \lambda_{wi}, \cdot] = \Pr[u_{\pi ij} \in (\mu_{\pi_{ij}} - \boldsymbol{q}_{ij}'\widetilde{\boldsymbol{\alpha}}_\pi - \boldsymbol{z}_{Ai}'\boldsymbol{\gamma}_\pi - \boldsymbol{x}_i'\boldsymbol{\kappa}_\pi - \lambda_{\pi i}, \mu_{\pi_{ij}+1} -$$

$$\boldsymbol{q}_{ij}'\widetilde{\boldsymbol{\alpha}}_\pi - \boldsymbol{z}_{Ai}'\boldsymbol{\gamma}_\pi - \boldsymbol{x}_i'\boldsymbol{\kappa}_\pi - \lambda_{\pi i}], u_{wij} \in (\nu_{w_{ij}} - \boldsymbol{q}_{ij}'(\widetilde{\boldsymbol{\alpha}}_w + \widetilde{\boldsymbol{\alpha}}_\pi\delta_{wi}) - \boldsymbol{z}_{Ai}'\boldsymbol{\gamma}_\pi\delta_{wi} -$$

$$\boldsymbol{z}_{Bi}'\boldsymbol{\gamma}_w - \boldsymbol{x}_i'(\boldsymbol{\kappa}_w + \boldsymbol{\kappa}_\pi\delta_{wi}) - \lambda_{wi} - \lambda_{\pi i}\delta_{wi}, \nu_{w_{ij}+1} - \boldsymbol{q}_{ij}'(\widetilde{\boldsymbol{\alpha}}_w + \widetilde{\boldsymbol{\alpha}}_\pi\delta_{wi}) -$$

$$\boldsymbol{z}_{Ai}'\boldsymbol{\gamma}_\pi\delta_{wi} - \boldsymbol{z}_{Bi}'\boldsymbol{\gamma}_w - \boldsymbol{x}_i'(\boldsymbol{\kappa}_w + \boldsymbol{\kappa}_\pi\delta_{wi}) - \lambda_{wi} - \lambda_{\pi i}\delta_{wi}]|\lambda_{\pi i}, \lambda_{wi}, \cdot]. \tag{A.9}$$

The expression $\Pr[u_{\pi ij} \in (\cdot,\cdot], u_{wij} \in (\cdot,\cdot]|\lambda_{\pi i}, \lambda_{wi}, \cdot]$ in Eq. (A.9) defines a rectangular region of integration for the bivariate normal probability density function of $u_{\pi ij}$ and u_{wij}, as implied by Eq. (A.4); it is evaluated numerically, using an existing algorithm (see Genz, 2004).

Eq. (A.9) is applicable when neither the interest premium response, nor the deposit withdrawal response of respondent i for profile j is missing. Such cases (i.e., $\pi_{ij} \neq$ -1 and $w_{ij} \neq$ -1) comprise the predominant majority of respondent-profile records (namely, 2,717 cases out of 2,792 respondent-profile records in total, or 97.31% of the total). When only the interest premium response is missing (i.e., π_{ij} = -1, but $w_{ij} \neq$ -1; there are 45 such cases, or 1.61% of the total), the conditional probability described by Eq. (A.9) takes the following special form:

$$\Pr[w_{ij}|\lambda_{\pi i},\lambda_{wi},\cdot] = \Pr[u_{wij} \in (\nu_{w_{ij}} - \boldsymbol{q}'_{ij}(\widetilde{\boldsymbol{\alpha}}_w + \widetilde{\boldsymbol{\alpha}}_\pi\delta_{wi}) - \boldsymbol{z}'_{Ai}\boldsymbol{\gamma}_\pi\delta_{wi} - \boldsymbol{z}'_{Bi}\boldsymbol{\gamma}_w - \boldsymbol{x}'_i(\boldsymbol{\kappa}_w + \boldsymbol{\kappa}_\pi\delta_{wi}) - \lambda_{wi} - \lambda_{\pi i}\delta_{wi}, \nu_{w_{ij}+1} - \boldsymbol{q}'_{ij}(\widetilde{\boldsymbol{\alpha}}_w + \widetilde{\boldsymbol{\alpha}}_\pi\delta_{wi}) - \boldsymbol{z}'_{Ai}\boldsymbol{\gamma}_\pi\delta_{wi} - \boldsymbol{z}'_{Bi}\boldsymbol{\gamma}_w - \boldsymbol{x}'_i(\boldsymbol{\kappa}_w + \boldsymbol{\kappa}_\pi\delta_{wi}) - \lambda_{wi} - \lambda_{\pi i}\delta_{wi}]|\lambda_{\pi i},\lambda_{wi},\cdot]. \tag{A.10}$$

Eq. (A.10) defines an interval of integration for the probability density function of a normal random variable $u_{wij}|\lambda_{\pi i},\lambda_{wi},\cdot \sim N(0,\delta_{wi}^2 + 2\rho_{\pi w}\sigma_w\delta_{wi} + \sigma_w^2)$. In turn, when only the deposit withdrawal response is missing (i.e., w_{ij} = -1, but $\pi_{ij} \neq$ -1; there are 14 such cases, or 0.50% of the total), the conditional probability becomes:

$$\Pr[\pi_{ij}|\lambda_{\pi i},\lambda_{wi},\cdot] = \Pr[u_{\pi ij} \in (\mu_{\pi_{ij}} - \boldsymbol{q}'_{ij}\widetilde{\boldsymbol{\alpha}}_\pi - \boldsymbol{z}'_{Ai}\boldsymbol{\gamma}_\pi - \boldsymbol{x}'_i\boldsymbol{\kappa}_\pi - \lambda_{\pi i}, \mu_{\pi_{ij}+1} - \boldsymbol{q}'_{ij}\widetilde{\boldsymbol{\alpha}}_\pi - \boldsymbol{z}'_{Ai}\boldsymbol{\gamma}_\pi - \boldsymbol{x}'_i\boldsymbol{\kappa}_\pi - \lambda_{\pi i}]|\lambda_{\pi i},\lambda_{wi},\cdot]. \tag{A.11}$$

Eq. (A.11) defines an interval of integration for the density function of a standard normal random variable $u_{\pi ij}|\lambda_{\pi i},\lambda_{wi},\cdot \sim N(0,1)$. When both responses are missing (π_{ij} = -1 and w_{ij} = -1; there are 16 such cases, or 0.57% of the total), we set the conditional probability equal to one.

The expressions derived above provide formulas to compute the likelihood contribution for every respondent in our sample. Assuming that the data across different respondents are i.i.d., the model parameters can be estimated by the maximum likelihood method:

$$\widehat{\boldsymbol{\Phi}}_{MLE} = \arg\max_{\boldsymbol{\Phi}} \textstyle\sum_{i=1}^n \ln L_i(\boldsymbol{\Phi}). \tag{A.12}$$

The variance-covariance matrix of $\widehat{\boldsymbol{\Phi}}_{MLE}$ is calculated by the BHHH method (Berndt et al., 1974). To ensure that the constraints imposed on the parameters hold, we re-parameterize the model prior to estimation, and obtain standard errors of the original parameters by the delta method. Statistical inference and hypothesis testing are then performed using conventional techniques (see Greene, 2012, Ch. 14).

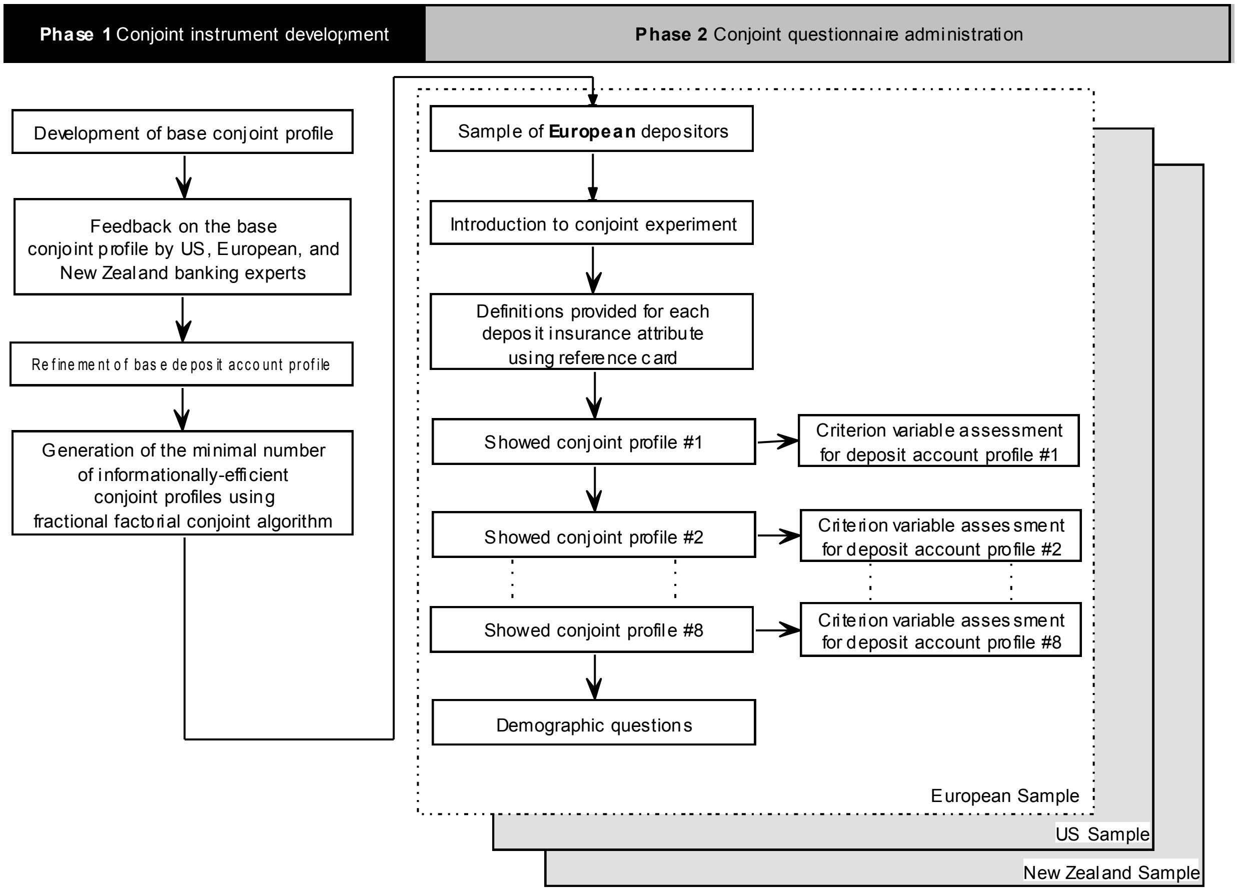

Fig. 1 Data collection overview

Table 1
Account profiles used in the survey instrument

Profile Attribute	Account Profile							
	1	2	3	4	5	6	7	8
Coverage limit	$50,000	$250,000	$250,000	$50,000	$50,000	$50,000	$250,000	$250,000
Deposit size	Above limit	Above limit	Above limit	Above limit	At or below limit	At or below limit	At or below limit	At or below limit
Guaranteed payout percentage	75%	100%	75%	100%	75%	100%	75%	100%
Deposit insurance premium type	Flat-rate	Flat-rate	Risk-adjusted	Risk-adjusted	Flat-rate	Risk-adjusted	Risk-adjusted	Flat-rate
Bank contributes to insurance fund	Yes	No	No	Yes	No	No	Yes	Yes
Insurance system membership	Compulsory	Voluntary	Compulsory	Voluntary	Voluntary	Compulsory	Voluntary	Compulsory
Capital buffer level	Above average	Above average	At or below average	At or below average	At or below average	Above average	Above average	At or below average

Notes. This table describes the eight hypothetical bank account profiles used in the survey instrument. Each profile has seven attributes. Each attribute has two levels. The profiles are generated using a conjoint algorithm implemented in SPSS 11.5.

Table 2
Description of variables used to identify account and respondent characteristics

Variable Name	Description
D_i	1 if respondent *i*'s home country does not have explicit deposit insurance (0 if it does)
Account characteristics	
High DI limit	1 if deposit insurance coverage limit is $250,000 (0 if $50,000)
No co-insurance	1 if guaranteed payout percentage is 100% (0 if 75%)
Large deposit	1 if deposit size exceeds the coverage limit
Pre-funded DI	1 if bank contributes to a deposit insurance fund
High buffer capital	1 if the level of bank's buffer capital is above average
Respondent characteristics	
Male	1 if respondent is male
Bank account ≥ 5 years	1 if respondent has had an actual deposit account for 5 or more years
Multiple bank relationships	1 if respondent has two or more additional relationships (e.g., a loan), besides the actual deposit account, with his or her bank
Peer influence	1 if respondent opened his or her actual deposit account on the advice of another bank customer
Risk tradeoff-low	1 if respondent disagrees or strongly disagrees with Risk Tradeoff statement (baseline category)
Risk tradeoff-below average	1 if respondent somewhat disagrees with Risk Tradeoff statement
Risk tradeoff-average	1 if respondent is neutral with respect to Risk Tradeoff statement
Risk tradeoff-above average	1 if respondent somewhat agrees with Risk Tradeoff statement
Risk tradeoff-high	1 if respondent agrees or strongly agrees with Risk Tradeoff statement
Risk tolerance-low	1 if respondent disagrees or strongly disagrees with Risk Tolerance statement (baseline category)
Risk tolerance-below average	1 if respondent somewhat disagrees with Risk Tolerance statement
Risk tolerance-average	1 if respondent is neutral with respect to Risk Tolerance statement
Risk tolerance-above average	1 if respondent somewhat agrees with Risk Tolerance statement
Risk tolerance-high	1 if respondent agrees or strongly agrees with Risk Tolerance statement

Table 3
Summary statistics for respondent characteristics

Variable	Full Sample		Subsample: $D_i = 0$		Subsample: $D_i = 1$		Equal Proportions Test	
	Mean	SD	Mean	SD	Mean	SD	*z*-statistic	*p*-value
Male	0.61	0.49	0.60	0.49	0.64	0.48	-0.81	0.42
Bank relationship ≥ 5 years	0.66	0.48	0.71	0.46	0.56	0.50	2.75	0.01
Multiple bank relationships	0.45	0.50	0.51	0.50	0.33	0.47	3.14	0.01
Peer influence	0.28	0.45	0.24	0.42	0.38	0.49	-2.87	0.00
Risk tradeoff-low	0.23	0.42	0.24	0.42	0.21	0.41	0.55	0.58
Risk tradeoff-below average	0.16	0.37	0.15	0.36	0.19	0.40	-0.99	0.32
Risk tradeoff-average	0.12	0.33	0.11	0.31	0.16	0.36	-1.33	0.18
Risk tradeoff-above average	0.27	0.45	0.28	0.45	0.25	0.44	0.59	0.56
Risk tradeoff-high	0.21	0.41	0.23	0.42	0.19	0.40	0.75	0.45
Risk tolerance-low	0.31	0.46	0.28	0.45	0.37	0.48	-1.67	0.10
Risk tolerance-below average	0.23	0.42	0.24	0.42	0.21	0.41	0.10	0.58
Risk tolerance-average	0.18	0.39	0.19	0.39	0.17	0.38	0.32	0.75
Risk tolerance-above average	0.16	0.36	0.18	0.39	0.10	0.31	1.91	0.06
Risk tolerance-high	0.13	0.33	0.12	0.32	0.15	0.36	-0.86	0.39
N	349		234		115		—	

Notes. D_i = 0 (1) if respondent *i*'s home country does (does not) have explicit deposit insurance. All variables are dummies, as defined in Table 2. For each variable, the final two columns report the *z*-statistic and corresponding *p*-value for the null hypothesis of equality between the subsamples.

Table 4
Distribution of responses to interest premium question

Response	Full Sample (%)	Subsample: $D_i = 0$ (%)	Subsample: $D_i = 1$ (%)
1. Significantly lower	4.26	5.18	2.39
2	9.20	10.68	6.20
3	13.72	14.00	13.15
4	14.90	15.33	14.02
5	17.26	17.20	17.39
6	15.72	15.12	16.96
7	12.61	10.47	16.96
8	6.81	6.30	7.83
9. Significantly higher	3.33	2.56	4.89
-1: Missing	2.18	3.15	0.22
N	2,792	1,872	920
Pearson χ^2 test:	$\chi^2(9)$ statistic=84.16, p-value=0.00		

Notes. This table presents the distribution of responses (pooled across the eight account profiles) to the question "*Compared to competing financial institutions, I would expect an annualized interest rate for this account to be…*" Responses could range from significantly lower (1) to significantly higher (9). D_i = 0 (1) if respondent i's home country does (does not) have explicit deposit insurance.

Table 5
Distribution of responses to deposit withdrawal question

Response	Full Sample (%)	Subsample: $D_i = 0$ (%)	Subsample: $D_i = 1$ (%)
0%	22.67	24.20	19.57
10%	6.91	6.89	6.96
20%	11.32	10.90	12.17
30%	10.78	11.06	10.22
40%	8.42	8.76	7.72
50%	10.85	9.99	12.61
60%	5.30	5.40	5.11
70%	7.56	7.16	8.37
80%	5.73	5.24	6.74
90%	2.72	2.78	2.61
100%	6.66	6.09	7.83
-1: Missing	1.07	1.55	0.11
N	2,792	1,872	920
Pearson χ^2 test:	$\chi^2(11)$ statistic=30.33, p-value=0.00		

Notes. This table presents the distribution of responses (pooled across the eight account profiles) to the question "*On hearing about the news of the shock to the financial system, what percentage of your deposit are you likely to immediately withdraw?*" Responses could range from 0% to 100%. D_i = 0 (1) if respondent i's home country does (does not) have explicit deposit insurance.

Table 6

Regression model of respondent reaction to the failure of a major domestic bank

	Dependent Variable			
	Interest Premium		*Deposit Withdrawal*	
Explanatory Variable	Coefficient	Std. Error	Coefficient	Std. Error
D_i	0.73***	0.18	33.62***	7.60
Account attributes $\boldsymbol{p}_j$				
High DI limit	-0.18**	0.08	-4.64	2.88
No co-insurance	-0.22**	0.09	-9.92***	2.34
Large deposit	0.44***	0.06	31.66***	2.36
Pre-funded DI	0.02	0.09	4.76*	2.60
High buffer capital	-0.20**	0.09	-5.88*	3.51
Interactions $D_i \times \boldsymbol{p}_j$				
D_i × High DI limit	-0.01	0.14	1.25	4.86
D_i × No co-insurance	-0.33**	0.15	-18.60***	4.24
D_i × Large deposit	0.02	0.12	-8.90***	3.26
D_i × Pre-funded DI	-0.27	0.17	-9.87**	4.73
D_i × High buffer capital	-0.01	0.15	-3.94	5.50
Respondent background characteristics $\boldsymbol{x}_i$				
Male	0.05	0.05	-1.46	1.28
Bank account ≥ 5 years	0.11***	0.04	-7.30***	1.32
Multiple bank relationships	0.01	0.04	1.40	1.08
Peer influence	-0.02	0.05	1.93	1.18
Risk tradeoff characteristics $\boldsymbol{z}_{Ai}$				
Risk tradeoff-below average	-0.02	0.06		
Risk tradeoff-average	-0.12*	0.06		
Risk tradeoff-above average	0.24***	0.05		
Risk tradeoff-high	0.11**	0.05		
Risk tolerance characteristics $\boldsymbol{z}_{Bi}$				
Risk tolerance-below average			2.84**	1.39
Risk tolerance-average			3.59**	1.63
Risk tolerance-above average			-0.68	1.58
Risk tolerance-high			-4.85***	1.75
Latent interest premium			1.16	4.56
Latent interest premium × D_i			-4.55***	1.48
Constant	1.76***	0.28	25.34***	8.26

Notes. This table presents the estimated system described by Eqs. (3) and (4):

$$\pi_{ij}^* = \theta_\pi \cdot D_i + \boldsymbol{p}_j' \cdot \boldsymbol{\alpha}_\pi + D_i \cdot \boldsymbol{p}_j' \cdot \boldsymbol{\beta}_\pi + \boldsymbol{z}_{Ai}' \cdot \boldsymbol{\gamma}_\pi + \boldsymbol{x}_i' \cdot \boldsymbol{\kappa}_\pi + \lambda_{\pi i} + \epsilon_{\pi ij},$$

$$w_{ij}^* = \theta_w \cdot D_i + \boldsymbol{p}_j' \cdot \boldsymbol{\alpha}_w + D_i \cdot \boldsymbol{p}_j' \cdot \boldsymbol{\beta}_w + \boldsymbol{z}_{Bi}' \cdot \boldsymbol{\gamma}_w + \boldsymbol{x}_i' \cdot \boldsymbol{\kappa}_w + \pi_{ij}^* \cdot \delta_{wi} + \lambda_{wi} + \epsilon_{wij},$$

where π_{ij}^* is the latent interest premium, w_{ij}^* is the latent deposit withdrawal percentage, $D_i = 0$ (1) if respondent *i*'s home country does (does not) have explicit deposit insurance, and $\delta_{wi} = \delta_w + \Delta_w D_i$. See Table 2 for other variable definitions. Statistical significance: $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Each equation also includes dummies for risk-adjusted, and compulsory bank participation in, deposit insurance, but these are suppressed to conserve space as they have little effect on the two dependent variables. The number of observations for each of the two dependent variables is 2,792 (349 responses to eight questions).

Table 7
Actual and predicted incidence of deposit withdrawal responses

Withdrawal Percentage	Full Sample		Subsample: $D_i = 0$		Subsample: $D_i = 1$	
	Actual	Predicted	Actual	Predicted	Actual	Predicted
< 10%	0.23	0.21	0.25	0.22	0.20	0.19
≥ 10%	0.77	0.79	0.75	0.78	0.80	0.81
	χ^2=0.67, p=0.41		χ^2=0.77, p=0.38		χ^2=0.03, p=0.87	
< 20%	0.30	0.31	0.32	0.32	0.27	0.28
≥ 20%	0.70	0.69	0.68	0.68	0.73	0.72
	χ^2=0.10, p=0.74		χ^2=0.01, p=0.91		χ^2=0.17, p=0.68	
< 30%	0.41	0.42	0.43	0.43	0.39	0.39
≥ 30%	0.59	0.58	0.57	0.57	0.61	0.61
	χ^2=0.03, p=0.86		χ^2=0.02, p=0.90		χ^2=0.01, p=0.91	

Notes. This table presents actual and predicted incidence of responses to the deposit withdrawal question. "Actual incidence" refers to the fraction of actual responses indicating a specified withdrawal percentage (e.g., < 10%), averaged across the eight account profiles. "Predicted incidence" refers to the corresponding fraction predicted by our model. The χ^2 statistics and associated p-values (denoted as p) refer to tests of the hypothesis that the actual and predicted distributions of the responses are the same. D_i = 0 (1) if respondent i's home country does (does not) have explicit deposit insurance.