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The rate elasticity of retail deposits in the United Kingdom: a macroeconomic investigation

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Abstract

This paper quantitatively studies the behaviour of major banks' household deposit funding in the United Kingdom. We estimate a panel of Bayesian vector autoregressive models on a unique data set compiled by the Bank of England, and identify deposit demand and supply shocks, both to individual banks and in aggregate, using micro-founded sign restrictions. Based on the impulse responses, we estimate how much banks would be required to increase their deposit rates by to cover a deposit gap caused by funding shocks. Banks generally find it costly to bid-up for deposits to cover a funding gap in the short run. The elasticity of household deposits with respect to the interest rate paid are typically of the order of 0.3, indicating that retail deposits are rate-inelastic. But this varies across banks and the types of shock conditioned on. We also show evidence that banks are more vulnerable to deposit supply shocks than deposit demand shocks. Historical decompositions uncover plausible shock dynamics in the historical data.

Key words: Retail deposits behaviour, Bayesian panel-VAR, sign restrictions.

JEL classification: C11, E40, G21.

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1 Introduction

The global financial crisis highlighted fragilities in wholesale funding markets, and at intermediaries in those markets on which banks depended for wholesale funding. In September 2007 Northern Rock fell victim to the first run on a bank in the UK since 1878 when it lost access to the wholesale markets on which it relied for funding, see Shin (2009). Elevated funding costs have remained a key issue for bankers and policy makers in recent years, as highlighted by a recent Bank of England publication, see Beau, Hill, Hussain and Nixon (2014). At least partly in response to funding pressures, a number of banks in the United Kingdom have reviewed their business models and activities, leading to significant changes to their balance sheets and funding structures: banks have reduced their reliance on wholesale funding by financing more of their assets with deposits. The introduction of new liquidity standards under Basel III – the Liquidity Coverage Ratio (LCR) and Net Stable Funding Ratio (NSFR) – also incentivise banks to grow their share of retail deposits (retail funding) at the expense of wholesale funding.[1]

As a result of these changes, it has become increasingly important for policy-makers to be able to assess the stability of deposit bases against a range of shocks, both to individual banks and in aggregate, as banks transition towards their new steady-state funding structures. While a large body of existing literature highlights risks posed by *wholesale funding* (e.g. Acharya, Gale and Yorulmazer (2011)), we seek to draw attention to risks that *retail funding* may pose to individual banks and to the banking system as a whole.

This paper contributes to the literature by quantitatively studying the behaviour of household deposit funding at major UK banks using an empirical macroeconomic methodology. We exploit a unique dataset, compiled by the Bank of England, covering deposit rates and deposit balances for UK banks. The data are monthly and cover the period from January 2004 to December 2013. Together with other time series data, we estimate a panel of linear Bayesian vector-autoregression (BVAR) regression models employing 'hierarchical priors' as described in Jarocinski (2010). These priors allow us to pool short sample data during estimation, while preserving dynamic heterogeneity across banks.

To identify structural shocks in the household deposits market, we adopt an 'agnostic' approach along the lines of Faust (1998), Canova and De Nicolo (2002), and Uhlig (2005). We

[1] By way of illustration, under the LCR just 5% of stable retail deposits are assumed to run during the first 30 days following a stress. In contrast, the rate at which unsecured wholesale funding runs is assumed to be in the range of 75-100%.

identify shocks by imposing a set of unique micro-founded contemporaneous sign restrictions when estimating the panel of BVARs. These restrictions are provided by a stylised, one-period linear partial equilibrium model. The model characterises the behaviour of a representative household that supplies (retail) deposits to the banking system, and optimally allocates them across individual banks. The model also captures individual banks' optimal demand for retail deposits. This paper simultaneously studies four types of structural shock: (i) idiosyncratic retail deposit demand shock; (ii) aggregate retail deposit demand shock; (iii) idiosyncratic retail deposit supply shock; and (iv) aggregate retail deposit supply shock. The first two shocks work via the banking sector, whereas the latter come from the household sector.

The empirical model is estimated over the full sample (January 2004 - December 2013). To account for possible structural changes in banks' behaviour following the onset of the global financial crisis, we also conduct split sample analysis. We identify June 2007 as a structural break in retail deposit markets (shortly before the crisis at Northern Rock). Mindful that the pre-crisis sample (January 2004 – June 2007) may be too short for estimation, we estimate the post-crisis sample (July 2007 – December 2013), and proceed to report and compare these results against data from the full sample. Based on the impulse responses, we construct a measure called 'required average increase in deposit rate' (RAIDR). This is a dynamic measure designed to quantify how much banks would have had to bid-up their deposit rate by, in order to raise some fixed quantity of deposits in response to a shock. To adjust for differences in the pre-crisis and post-crisis periods, we also introduce a measure of the elasticity of household deposits with respect to the deposit rate to facilitate time-consistent comparisons.

Post-crisis sample estimates across banks and shocks suggest that in order to raise £1 billion of retail deposits, banks face a median RAIDR in the order of 5 basis points (bps) at the 12-month horizon, 10bps at the 6-month horizon, and 20 bps at the 3-month horizon: As expected, the RAIDR is generally decreasing in the length of the time horizon. This implies that when banks are able to cover their deposit gap with less urgency, they are able to raise their deposit rates by less than when they are forced to cover the gap over a shorter horizon.

In terms of elasticities, we find that household retail deposits in the UK are rate-inelastic. Post-crisis sample estimates show that elasticities lie in the range of 0.1 to 0.5 at the 12-month horizon. Moreover, our results show that elasticities conditional on deposit demand shocks are larger than those conditional on deposit supply shocks, suggesting that banks find it more difficult to use deposit rates to mitigate deposit supply shocks.

By comparing the differences in the impulse responses and the computed metrics in the full and post-crisis samples, our estimates indirectly show that retail deposit behaviour differs before and after the financial crisis. For example, the rate-elasticity of retail deposits appears to have increased slightly following the financial crisis.

Collectively, our findings suggest that a retail-deposit funded bank may find it difficult (and costly) to attract deposit inflows quickly, but is increasingly able to mitigate shocks when it can raise retail deposits over longer horizons. This implies that retail-funded banks may need alternative means of managing shocks (such as adequate liquidity coverage) in place to ensure they can ride-out cyclical shocks in the short-run. Moreover, our results suggest that policy-makers and regulators should give further consideration to the impact of deposit supply shocks as we find that banks are more vulnerable to this type of shock.

Our paper contributes to a growing body of empirical literature that seeks to study bank funding behaviour. Damar, Meh and Terajima (2013, 2015) study how wholesale funding can lead to bank procyclicality and the relevant implications to the real economy. Craig and Dinger (2013) relate deposit market competition to wholesale market conditions and examine their joint effect of the risk of bank assets. De Haan, van den End and Vermeulen (2014) use a panel BVAR to study the response of European banks' lending (volumes and rates) to wholesale funding shocks, identified by Cholesky decomposition. Our paper differs from theirs in that we focus on *retail funding*, and model retail deposit supply and demand shocks, and that our BVAR analysis omits lending data, due to data constraints and to ensure tractability. Perhaps closest to our paper is De Greave and Karas (2014): using Russian deposits market data, they identify 'bank run shocks' by imposing both sign and heterogeneity restrictions. Our paper takes a step further by identifying a full set of deposit demand and supply shocks using sign restrictions.

This paper is also related to a large empirical literature studying retail banking activities. De Bondt (2002) provides evidence on retail bank interest rate pass-through using a VECM framework. McQuinn and Woods (2012) model Irish financial institutions' corporate deposits using an error-correction model to infer long-run and short-run dynamics. Rughoo and Saranti (2014) investigate how the European Union retail banking sector is integrated by studying deposit and lending rates to the household sector before and after the Global Financial Crisis. Corvoisier and Gropp (2002) study whether bank pricing has become more competitive using micro-level bank data in the Euro area, whereas Heffernan (2002) studies the price-setting behaviour in the UK banking sector.

There is also a significant body of theoretical work which seeks to model retail deposit markets and infer the behaviour of household deposits. Diamond and Dybvig (1983) provides a classic reference on bank-runs. Salop (1979) models bank competition spatially: 'services' provided by each branch are a function of the spatial distance from where the household is located. Klemperer (1989) explains how switching costs affect the competitiveness of markets, the theory of which is applied to the market for bank deposits by Sharpe (1997). Bruche and Suarez (2009) present a theoretical model that captures how deposit insurance can create asymmetry between 'savings rich' and 'savings poor' regions which can lead to a freeze in the money market. While the literature tends to focus on identifying either deposit demand or supply shocks, this paper constructs a theoretical model to *simultaneously* identify structural demand and supply shocks in the deposits market.

The rest of the paper is structured as follows. Section 2 describes the theoretical model that we use to select the sign restrictions. Section 3 introduces the dataset and provides a discussion of the panel of BVARs as a hierarchical model. Sections 4-6 present results and discussion of policy implications, followed by robustness checks. Section 7 concludes the paper with some discussion of future work.

2 The theoretical model

The theoretical model introduced in this section is used to provide a set of micro-founded sign restrictions for structural shock identification in the empirical estimation. The aim is to derive a set of micro-founded sign restrictions to uniquely identify the demand and supply shocks of interest in the data. By adopting a number of assumptions, we construct a *linear, one-period, partial equilibrium* model featuring a representative household (supplier of deposits) and heterogenous banks (demanders of deposits).[2]

2.1 The household's optimisation problem

The representative household is risk averse and takes all interest rates as given. It is endowed with some initial wealth, which is divided between cash (governed by an exogenous 'liquidity preference' parameter) and non-cash assets. It then optimally allocates its non-cash wealth to

[2]Hereonin, household deposits are referred to simply as 'deposits'.

some combination of a risky asset (e.g. equities) and a risk-free asset – funds deposited at banks. This stylised set-up provides a framework in which to study how households rebalance their non-cash wealth portfolio between risky assets and risk-free deposits.

2.1.1 Supply of aggregate deposits

The household seeks to maximise the risk-adjusted return of its portfolio, given an initial allocation of non-cash wealth. Deposits are treated as the risk-free asset in our set-up – reflecting an implicit assumption that all household deposits are covered by deposit insurance.[3]

Given an initial allocation of wealth w, the household allocates a proportion φ to cash and $1-\varphi$ to non-cash assets, where φ is an exogenous parameter governing the household's liquidity preference. An exogenous increase in φ causes a household to prefer to hold more cash – perhaps due to a loss of confidence in the banking system. Denote non-cash wealth as $w^{nc} = (1-\varphi)\,w$.

A simple portfolio choice problem is modelled. Given an allocation of non-cash wealth, the household invests in a portfolio comprising a risky asset and risk-free bank deposits. We denote s_r as the share of wealth invested in risky assets, and s_f as the share of wealth invested in risk-free deposits. By definition, $s_r + s_f = 1$. Denote $R_r \sim d\,(\mu_r, \sigma_r)$ as the random return of the risky asset, and $\overline{r}$ as the aggregate return for the risk-free deposits defined in the next subsection.[4] The end-of-period expected portfolio return R_p can be written as:

$$R_p = \overline{r}s_f + R_r s_r \tag{1}$$

We find s_r by exploiting the fact that the variance of the risk-free return is zero. Based on (1), the variance of end-of-period wealth is:

$$\sigma_p^2 = \sigma_r^2 s_r^2$$

implying:

$$s_r = \frac{\sigma_p}{\sigma_r} \tag{2}$$

Given non-cash wealth and the standard deviation of returns on the risky asset, the household chooses to invest a larger share of its wealth in the risky asset if it chooses to have a higher

[3]UK deposits made by private individuals to authorised firms have been protected by the Financial Services Compensation Scheme up to a limit of £85,000 from 31 December 2010, and the majority of UK household deposits are covered by this scheme.

[4]We assume that banks do not default and the household knows $\overline{r}$ for certain.

variance in the return on its portfolio. The share of wealth to be invested in the risk-free asset is then:

$$s_f = 1 - s_r = 1 - \frac{\sigma_p}{\sigma_r} \tag{3}$$

Denote D as the aggregate deposits supplied by the household. By definition, $D = s_f w^{nc} = s_f (1-\varphi) w$, and hence:

$$D = \left(1 - \frac{\sigma_p}{\sigma_r}\right)(1-\varphi) w \tag{4}$$

which specifies the aggregate supply of deposits[5] to the banking system from the household sector.[6]

Proposition 1 *Equation (4) implies* $\frac{\partial D}{\partial \sigma_p} < 0$, $\frac{\partial D}{\partial \varphi} < 0$

Proof. Results immediately follow from (4). ■

We interpret adverse **aggregate deposit supply shocks (Agg-DS shock)** as either (i) given a liquidity preference φ, the household prefers a riskier investment portfolio (an increase in σ_p), probably during times of benign macroeconomic conditions; or (ii) an exogenous increase in φ, resulting in the household preferring to hold more of its wealth as cash – perhaps following a drop in confidence in the banking system during times of financial instability.[7]

2.1.2 Supply of deposits to individual banks

We assume that there is a continuum of banks $i \in [0,1]$ which are monopolistic competitors and hence have a degree of monopoly power. Denote $\eta > 1$ as the elasticity of substitution across banks. The aggregate supply of deposits D is treated as a composite good, and is defined by the Constant Elasticity of Substitution (CES) aggregator:

[5]Equilibrium condition (4) gives us a condition that the aggregate supply of deposits D does not depend on the prevailing aggregate retail deposit rate $\overline{r}$ but on risk and liquidity preference parameters. This simplified condition helps us uniquely identify aggregate and idiosyncratic deposit supply shocks in the model. We stress that, as explained in the next subsection, the household's allocation of aggregate deposits across individual banks does indeed depend on each bank's deposit rate.

[6]Substituting (2) and (3) into (1) yields the opportunity set for one risky and risk-free asset: $R_p = \overline{r} + \sigma_p \frac{R_r - \overline{r}}{\sigma_r}$. In the (R_p, σ_p) space, the slope of the line is described by $\frac{R_r - \overline{r}}{\sigma_r}$, also known as the Sharpe ratio.

[7]Alternatively, we could have adopted a more comprehensive approach to model the optimal allocation among cash, risk-free deposits and risky assets for the household. However, it is likely that this more complicated approach will result in an identical shock identification scheme to the one documented in Table 1. Taking this into account, we opt for this more stylised modelling approach.

$$D = \left(\int_0^1 D_i^{1-\frac{1}{\eta}} di \right)^{\frac{1}{1-\frac{1}{\eta}}} \tag{5}$$

Denote r_i as the deposit rate offered by bank i, which the household takes as given. Also denote $\psi_i \geq 1$ as an exogenous parameter dictating how much the household likes/dislikes bank i's deposit 'service'. We may think about it as the cost to the consumer of travelling to the bank, or the quality of the bank's customer service.[8] This parameter serves to differentiate between banks by capturing non-price factors. The closer this value is to one, the more the household 'likes' that particular bank. The adjusted return a household receives from depositing with bank i is $\frac{r_i}{\psi_i}$. A household depositing $\frac{D_i}{(r_i/\psi_i)}$ will receive D_i at the end of the period. We interpret an increase in ψ_i as an adverse **idiosyncratic deposit supply shock (Id-DS shock)**.[9]

The household minimises its 'expenditure' on deposits subject to supplying a *given level of aggregate deposits.* It solves

$$\min_{D_i} \int_0^1 \left(\frac{\psi_i}{r_i} D_i \right) di$$

subject to (5).

Denote $\frac{1}{\overline{r}}$ as the Lagrange multiplier (or the shadow value) to the aggregate deposit constraint, where $\overline{r}$ is interpreted as the aggregate deposit rate. The Lagrangian reads

$$L = \int_0^1 \left(\frac{\psi_i}{r_i} D_i \right) di - \frac{1}{\overline{r}} \left[\left(\int_0^1 D_i^{1-\frac{1}{\eta}} di \right)^{\frac{1}{1-\frac{1}{\eta}}} - D \right]$$

The first order condition with respect to D_i gives:

$$D_i = \left(\frac{r_i/\psi_i}{\overline{r}} \right)^{\eta} D \tag{6}$$

The household's optimal supply of deposits to bank i is increasing in the adjusted interest rate relative to the aggregate deposit rate.

In equilibrium, the household will allocate its deposits across banks i and j according to the relative adjusted deposit rates:

[8] Note that this parameter is not endogenously linked to the health of the individual bank's balance sheet.

[9] This shock is a slightly more general than the 'bank run shock' in de Graeve and Karas (2014), that identifies bank run shocks as adverse deposit supply shocks that hit uninsured banks harder than insured ones in the Russian deposit market.

$$\frac{D_i}{D_j} = \left(\frac{r_i/\psi_i}{r_j/\psi_j}\right)^{\eta}$$

Substituting (6) into (5) gives the formula for the aggregate deposit rate $\overline{r}$:

$$\overline{r} = \left(\int_0^1 \left(\frac{r_i}{\psi_i}\right)^{\eta-1} di\right)^{\frac{1}{\eta-1}} \tag{7}$$

Proposition 2 *The aggregate supply of deposits from households is independent of the idiosyncratic deposit supply shock, i.e.* $\frac{\partial D}{\partial \psi_i} = 0$.

Proof. See Appendix. ■

2.2 Banks' optimisation problem

Recall that the banking system we model is comprised of a continuum of banks $i \in [0,1]$. To ensure that the modelling is tractable, and in light of data constraints, we make simplifying assumptions about the structure of banks' balance sheets. On the asset side, banks are assumed to hold a constant loan portfolio, L_i. Banks are not able to run down (liquid) assets in order to cover liquidity shocks; nor can they raise short-term secured funding by pledging collateral to the central bank. On the liabilities side, we assume that banks face a simple portfolio choice between household deposit funding, D_i, and 'other' funding, F_i. We abstract from modelling the maturity structure by assuming that all funding lasts for one period. Since this is a one-period model, banks face a static balance sheet and all household deposits can be raised in one period. All banks take the central bank's policy rate as given.

In combination, these assumptions mean that a bank can only respond to shocks by substituting between deposit funding and non-deposit/other funding.[10]

2.2.1 Demand for deposits

Each bank has monopoly power in setting the deposit rate $r_i(D_i)$ as it faces an upward sloping supply curve D_i (see (6)). The 'production' of deposits incurs a cost $C_i(D_i)$. The bank's marginal cost, $C_i'(D_i)$, is assumed to be increasing in D_i (i.e. $C_i''(D_i) > 0$).

[10]Our model does not allow a bank to increase its market share by, for example, building new branches, or improving its online/mobile banking service either, and hence we assume away banks' ability to influence the parameter ψ_i. We assume away any spillover effects (i.e. any impact of funding shocks from one bank to another) or bank defaults, and any policy responses from the central bank. We acknowledge the presence of non-linearities, but leave their modelling to future research.

For the purpose of illustration, we can think of 'other' funding as interbank borrowing. But the intuition developed in this section could be applied more generally to sources of funds that banks can use *instead* of retail deposits. The interest rate a bank i has to pay for interbank loans can be decomposed into two components: a global interbank rate $\widetilde{r}$ and a bank-specific spread s_i. Assume that the spread $s_i = s_i\left(z, \sigma_i^b\right)$,where $s_i'\left(\sigma_i^b\right) > 0$ and $s_i'(z) = \phi > 0$ across all banks. The parameter σ_i^b is interpreted as the idiosyncratic riskiness of interbank lending to bank i, whereas z is interpreted as the riskiness of the UK interbank system as a whole. By definition, this assumption implies that a change in z will cause the same change in spreads s_i for all banks i.

A change in σ_i^b corresponds to an **idiosyncratic deposit demand shock (Id-DD shock)**. Specifically, a rise in the value of σ_i^b is interpreted as an increase in the riskiness of lending to bank i in 'other' markets (e.g. interbank markets), prompting that particular bank to re-balance its liabilities portfolio away from 'other' funding, towards deposit funding. Moreover, this shock will also increase the bank spread s_i *for bank i only.* In contrast, an **aggregate deposit demand shock (Agg-DD shock)** is characterised by an increase in the common component z, which drives up bank spreads s_i *for all banks symmetrically*, *prompting all banks to demand additional deposits.*

Defining the average spread across banks $s = \int_0^1 s_i\left(z, \sigma_i^b\right) di$ and an individual bank's spread relative to the market average spread $\widetilde{s}_i = s_i - s$, we arrive at the following proposition:

Proposition 3 *It follows that* $\frac{\partial \widetilde{s}_i}{\partial z} = 0$ *and* $\frac{\partial \widetilde{s}_i}{\partial \sigma_i^b} > 0$ *for a particular bank i.*

Proof. See appendix. ■

This proposition states that the relative interbank spread for an individual bank goes up when it faces a bank-specific wholesale funding shock (a rise in σ_i^b), whereas the relative spread remains unchanged when the wholesale funding shock affects the banking system as a whole (a rise in z).

Bank i attempts to minimise its funding cost function, which includes the total cost of retail funding, wholesale funding and the cost of producing deposits, subject to the balance sheet constraint:

$$\min_{D_i, F_i} \nabla = r_i(D_i) D_i + \left(\widetilde{r} + s_i\left(z, \sigma_i^b\right)\right) F_i + C_i(D_i) \tag{8}$$

subject to:

$$L_i = D_i + F_i \tag{9}$$

The first order condition reads:

$$\frac{\partial r_i\left(D_i\right)}{\partial D_i} D_i + r_i\left(D_i\right) + C_i'\left(D_i\right) = \widetilde{r} + s_i\left(z, \sigma_i^b\right) \tag{10}$$

which implicitly defines the downward sloping demand for deposits of each bank i.

2.3 Retail deposits equilibrium and comparative statics

Equilibrium deposit rate r_i^* and deposit balance D_i^* for bank i can be found by solving (6) and (10), taking $\overline{r}$ and D as given. We derive comparative statics with respect to the parameters of interest in the model.

Proposition 4 *Based on the deposit equilibrium conditions for bank i, we derive the following comparative statics for its equilibrium level of deposits D_i^*:*

$$\frac{\partial D_i^*}{\partial \sigma_i^b} > 0, \frac{\partial D_i^*}{\partial z} > 0, \ \frac{\partial D_i^*}{\partial \psi_i} < 0, \frac{\partial D_i^*}{\partial \sigma_p} < 0, \frac{\partial D_i^*}{\partial \varphi} < 0$$

Proof. See appendix. ■

Proposition 5 *Based on the deposit equilibrium conditions for bank i, we derive the following comparative statics for its equilibrium deposit rate r_i^*:*

$$\frac{\partial r_i^*}{\partial \sigma_i^b} > 0, \frac{\partial r_i^*}{\partial z} > 0, \ \frac{\partial r_i^*}{\partial \psi_i} > 0, \frac{\partial r_i^*}{\partial \sigma_p} > 0, \ \frac{\partial r_i^*}{\partial \varphi} > 0$$

Proof. See appendix. ■

2.4 Sign restrictions for shock identification

The theoretical model and accompanying comparative statics provide a set of micro-founded restrictions to *uniquely* identify the *contemporaneous* effects brought about by the four types of structural shocks. Table 1 summarises the shock identification scheme, which can be described in words as:

- A deposit demand shock to an individual bank (Id-DD shock) is associated with an increase in the interbank spread of the bank relative to other banks in the system. The bank

Table 1: Summary of identifying restrictions

	Id-DD Shock ($\sigma_i^b \uparrow$)	Agg-DD shock ($z \uparrow$)	Id-DS Shock ($\psi_i \uparrow$)	Agg-DS Shock ($\sigma_p \uparrow, \varphi \uparrow$)
D_i	>0	>0	<0	<0
r_i	>0	>0	>0	>0
D	?	?	=0	<0
$\widetilde{s}_i$	>	=0	?	?

Note: D_i refers to bank i's stock of deposits, and r_i to its deposit rate D refers to aggregate household deposits, and $\widetilde{s}_i$ is bank i's 'other' funding spread, relative to the market average spread. '?' indicates no sign restriction.

responds by bidding up for deposits, closing the funding gap by attracting additional deposits.

- A deposit demand shock to the banking system in aggregate (Agg-DD shock) is defined as a parallel shift in all banks' interbank spreads. Under this definition, relative spreads between banks are unchanged. All other effects are similar to an Id-DD shock.

- A deposit supply shock to an individual bank leads to an outflow of deposits (Id-DS shock) and causes it to increase its deposit rate. The aggregate deposit level is not affected: outflows are assumed to be redistributed across the banking system.

- A deposit supply shock to the banking system in aggregate (Agg-DS shock) is similar in nature to the individual deposit supply shock – the only difference being the negative impact on aggregate deposits. The decrease in aggregate deposits can be caused by either: (i) households rebalancing their portfolios towards risky investments, typically in benign macroeconomic conditions; or (ii) households preferring to hold more cash, which could occur, for example, during a crisis of confidence in the banking system.

3 The empirical model

3.1 Panels of VARs as a hierarchical linear model

Vector autoregressive (VAR) models have been widely used in the empirical macro literature to model economic dynamics and identify structural shocks. As a researcher may also be interested in studying a group of heterogenous units (of the same underlying economic model), panel VARs which pool information across units have also been developed to make efficient use of scarce data for estimation.

Using $i = 1, ..., I$ to represent each bank, $j = 1, ..., p$ to represent the number of lags, and $t = 1, ..., T$ to represent the time dimension of the data, we specify the panel-VAR model as follows:

$$Y_{i,t} = \sum_{j=1}^{p} A_{i,j} Y_{i,t-j} + B_i X_t + C_i z_{i,t} + u_{i,t} \tag{11}$$

where $Y_{i,t} = [D_{i,t};\ r_{i,t};\ D_t;\ \widetilde{s}_{i,t}]'$ is a vector of four endogenous variables discussed in the theoretical model, X_t is a vector of exogenous variables common across banks, $z_{i,t}$ represents the bank-specific constant terms (bank fixed effects), and $u_{i,t} \sim N(0, \Sigma_i)$ are reduced form shocks. In this set-up, we assume away any static or dynamic interdependencies between banks, but we do preserve dynamic heterogeneity in the form of 'partial pooling'.

We propose the use of the hierarchical linear model of Gelman, Carlin, Stern and Rubin (2003), following Jarocinski (2010), for two reasons: the short data sample necessitates some form of pooling, and the assumption that bank coefficients shrink to some common mean is reasonable given the sample of banks under study.

The first stage of hierarchy is to formalise the idea of 'similarity'. An exchangeable prior is imposed which specifies that *banks' coefficients are assumed to be centred at a common mean.* This prior shrinks the bank coefficients to some common mean. The second stage of hierarchy involves the 'hypervariance', a hyperprior about the prior parameters: it governs the common mean and the variance of bank coefficients around the common mean.

The hierarchical linear model allows us to specify the priors in the second stage of the hierarchy as non-informative, and let the data inform the posterior mean and hypervariance, given the assumed likelihood and prior structure. A greater degree of heterogeneity in the estimated bank coefficients implies that the posterior probability of a large hypervariance will be higher. Bank models which are more tightly estimated receive relatively more weight in the posterior common mean, compared to those in which the estimates are less precise.

We specify non-informative priors for banks' fixed effects ($z_{i,t}$) and the common mean of the coefficients $A_{i,j}$ and B_i. Exchangeable priors are imposed for the endogenous variables ($Y_{i,t-j}$) and common exogenous variables (X_t). In line with Jarocinski (2010), each of the diagonal entries of the hypervariance matrix is specified by the coefficient's variance, adjusted for the size of the coefficient. All off-diagonal entries are set to zero. The variances are then scaled by a common variable λ, which determines the overall tightness of the exchangeable prior: $\lambda = 0$ results in full pooling of information across banks. Increasing λ allows each bank's model to be farther from the common mean. Our estimation supposes that there is some intermediate range for λ, and the underlying data play a role in determining the posterior distribution of λ which tends to be a very small number. We refer the reader to Jarocinski (2010) for more details.

3.2 Data and estimation details

3.2.1 Endogenous variables

The empirical estimation in this paper is based on a unique confidential dataset compiled by the Bank of England. Effective deposit rates and deposit balances are collected from a sample of institutions that collectively account for at least 75% of Sterling household deposits in the UK. Effective rates are calculated as a function of average loan/deposit balances and interest payable/receivable on those balances.[11] The estimation makes use of total household deposit data (i.e. the stock of household deposits) and effective household deposit rates. Individual banks' stocks of deposits are converted into monthly percent changes and become the variable D_i. Four banks are used in our analysis.

To control for the impact of monetary policy on deposit rates, we express deposit rates as a spread over the risk-free rate in our empirical implementation for r_i. Specifically, we define the deposit spread as the difference between the effective household deposit rate and the central bank policy rate (Bank rate).[12]

We use monthly percentage changes to household M4 to proxy for aggregate deposits D, rather than summing balances across banks.[13]This set-up allows for the interpretation of results in the most aggregate sense: responses to each bank are measured against the rest of the banking system, rather than just the other banks for which deposit balances are available.

The spreads on other funding, s_i, are proxied by 5-year Euro-denominated Senior CDS data. The average market spread is a simple average of CDS spreads across the banks. Table 2 summarises the data and the variables used.

[11] For more information on effective rates, see `http://www.bankofengland.co.uk/statistics/Pages/iadb/notesiadb/effective_int.aspx`.

[12] The model is partial equilibrium, and monetary policy is taken as given. This means that subtracting the Central Bank policy rate from the deposit rate results only in a change in the level. Neither the optimal conditions for deposit supply nor the comparative statics listed in proposition 5 are affected.

[13] Similar results are obtained if we simply sum balances across banks.

Table 2: List of variables and data

Variable	Data used for estimation for bank i
D_i	Monthly percent changes (growth rate) of individual bank deposit data (%)
r_i	Effective household deposit rate - Bank Rate (deposit spread,%)
D	Monthly percent changes of Household M4 (%)
$\widetilde{s}_i$	Individual bank's 5-year Euro Senior CDS data - average market spread (basis points)

Table 3: Summary statistics of the panel data on total retail deposits and rates

	Full sample (04M1-13M12)			**Post-crisis sample (07M7-13M12)**		
	Avg stock of deposits (£bn)	Avg rate paid on deposit stock (bps)	Avg mthly growth in stock (%)	Avg stock of deposits (£bn)	Avg rate paid on deposit stock (bps)	Avg mthly growth in stock (%)
Unweighted mean	127.4	210	0.80	138.8	170	0.40
Weighted mean	159.3	211	0.67	172.3	175	0.35

Source: Bank of England.
The weighted mean is computed by weighing the statistics by the individual bank's relative share of household deposits in the data samples. Four banks are included in the sample.

3.2.2 Control variables

We also include a selection of variables, X_t, in the regression in order to control for exogenous macroeconomic conditions on the retail deposit market. We include the Bank of England's policy rate and the monthly growth rate of GDP (as estimated by the National Institute of Economic and Social Research). To proxy for international wholesale funding conditions, we also include the 'Merrill Option Volatility Estimate' index which measures the implied interest rate volatility in the US market.

3.2.3 Estimation and shocks identification

We estimate the model using the full sample (Jan 2004 - Dec 2013) and the post-crisis sample (Jul 2007 - Dec 2013). Table 3 reports the summary statistics for the dataset. We resort to reporting averages in order to preserve the anonymity of banks.

We estimate the panel-VAR model (11) with six lags (i.e. $p = 6$). Each Gibbs simulation gives us estimates of the reduced-form innovations $u_{i,t}$ for each bank i. The shock identification scheme (Table 1) is imposed using Arias, Rubio-Ramirez and Waggoner (2013) on these innovations to identify the four structural shocks of interest, and to compute the impulse-response functions. For estimation, 1,020,000 draws are executed with the first 20,000 draws treated as burn-in. Every 1000th draw is retained for impulse response analysis and inference. Convergence is monitored following Geweke (1992).[14] Results with pooled-estimation and bank-by-bank estimation are discussed as robustness checks.

4 Impulse responses

The model developed in this paper allows us to investigate banks' endogenous responses to cyclical shocks, because impulse responses (functions of the panel BVAR coefficients and our structural shock identification) summarise the dynamic transmission of structural shocks.[15] Figure 1a illustrates a stylised deposit growth dynamic, where the *level* of deposit balances initially grows approximately log-linearly *in steady state.* Cyclical deposit demand or supply shocks create deposit gaps which a bank must close by raising addtitional deposits. Figure 1b shows a set of illustrative impulse responses fluctuating around the steady state trend growth. Deposit demand and deposit supply shocks hit at t_0, both of which require the banks to raise their deposit rates to bid-up for deposits. The growth rate of deposits deviates from trend temporarily, as a result of shocks and banks' mitigating actions, before returning to zero (i.e. no cyclical deviation) at time t_h. In this paper, we focus on studying the endogenous responses of retail deposit spreads and retail deposit growth rates.[16]

Figures 2 and 3 display the impulse responses of retail deposit spreads and deposit growth rates for an anonymous bank in the full and post-crisis data samples. Both variables are reported in the unit of percentage point (pp). The results are presented such that deposit growth is normalised on impact to *an increase of 1 percentage point for deposit demand shocks* (as in Figure 2), and to *a decrease of 1 percentage point for deposit supply shocks* (as in Figure 3). In other words, Figure 2 displays a scenario of *adverse wholesale* funding shocks which,

[14]For example, the posterior median of the distribution of $\sqrt{\lambda}$ centres at 2x10^{-5}, with standard deviation at 5x10^{-6}. Geweke (1992) proposes a Z-score, which tests whether the mean of the first 10% of The Markov chains and the mean of the last 50% of the sequence are equal, taking into account potential autocorrelation in the chain. In converged chains, Z-scores should have a standard normal distribution. The Z-score for λ in our estimation is not larger than 0.1 in both samples, hence indicating convergence.

[15]The system modelled is assumed to be at steady-state, absent cyclical shocks and with deposit stocks growing at some 'trend' rate. The emergence of cyclical shocks (impulses) perturbs the system, generating endogenous responses of modelled variables. Implicit in our modelling is the assumption that the cyclical shocks are small enough to be approximated by our linear empirical and theoretical models.

[16]Recall from Section 3 that the model set-up restricts banks' responses so that the interest rate paid on deposits is the only 'lever' banks can pull to mitigate the impact of these structural shocks.

in equilibrium, cause banks to attract more retail deposits by raising retail deposit spreads, whereas Figure 3 shows a scenario of adverse *retail* funding shocks which, in equilibrium, lead banks to increase their retail deposit spreads. Green lines denote the full-sample results. Black lines represent the post-crisis sample results.[17]

4.1 Deposit demand shocks

Figure 2 displays the impulse responses corresponding to idiosyncratic (top panel) and aggregate (bottom panel) deposit demand shocks. The response of deposit growth rate appears to be similar across the two samples for both shocks. The increase in deposit growth rate is not very persistent: growth rates quickly revert to their steady-state value. This is particularly true in the full sample.

4.2 Deposit supply shocks

Figure 3 shows evidence that growth in retail deposits in the post-crisis sample (black lines) is higher in the first six months after supply shocks hit. This difference is especially stark for idiosyncratic deposit supply shocks (top left panel), which show that this bank struggles to generate positive deposit growth in the full sample. It is also interesting to observe that this bank experiences a significant outflow of retail deposits six months after the supply shocks hit in both samples. Retail deposit spreads rise more on impact, but quickly revert to trend after six months in the post-crisis sample.

4.3 General discussion

Impulse responses across banks display heterogeneity in the level and degree of significance.[18] Interestingly, the shapes of the responses are consistently different between data samples – as seen in Figures 2 and 3. This indirectly suggests that deposit behaviour is structurally different before and after the financial crisis.

Two reasons potentially explain the differences across the samples: (i) The composition of banks' funding has changed as bank's business models have changed following the global financial crisis; and (ii) the degree of household risk aversion rose sharply during the crisis and

[17] The use of sign restrictions can only identify the size of shocks up to a proportional constant because of its set-identification properties, i.e. it admits a set of models satisfying the sign restrictions. We are not able to compare the size of structural shocks across banks.

[18] Impulse responses for the other three banks are shown in a separate chart appendix.

has been slow to unwind. As a result, aggregate deposit supply is likely to be less constrained in the post-crisis period.

We transform these dynamic responses into two metrics in the following section to aid our interpretation of them.

5 Two computed metrics based on impulse responses

The sensitivity of deposit balances to changes in deposit rates is relevant for the likely evolution of banks' funding costs, and hence the future profitability of banks. If the sensitivity varies significantly across different shocks, this would be useful information to provide to policy makers for the purpose of assessing the riskiness of deposit bases in different scenarios, as well as informing quantitative models of bank resilience (including stress tests). To address questions of this nature, we introduce two new metrics that capture the sensitivity of deposit balances to deposit rates: the *required average increase in deposit rate*, and the *dynamic deposit elasticity with respect to the deposit rate*. Both metrics are based on impulse responses.[19]

5.1 Required average increase in deposit rate

When a bank raises its deposit rate to mitigate the effect of a cyclical shock, a key question to ask is by how much a bank has to bid up its average deposit rate to close the 'funding' gap over a certain horizon. We call this the *required average increase in deposit rate* (RAIDR). Conditional on a structural shock and a horizon of h months, RAIDR is computed by:

$$RAIDR_h = \frac{Average\ change\ in\ deposit\ \ rates\ over\ h\ months\ (in\ bps)}{Cumulative\ change\ in\ deposits\ over\ h\ months\ (\pounds bn)} \tag{12}$$

For visual comparison, we plot RAIDRs across the full range of the time horizon to form RAIDR curves. We consider the horizon h to be 3, 6, 9 and 12 months.[20]

[19]It is important to note that both metrics are computed based on the cyclical increase in the stock of deposits; the trend growth of deposits is excluded from these calculations.

[20]We also consider a slight variant of RAIDR curves normalised by *one percent* of the average size of the stock of deposits of the bank over each sample. This is to take into account of the relative size of household deposit stocks (market share of deposits) held by each bank. Since the results are very similar, we report them in a separate chart appendix.

5.2 Dynamic deposit elasticities

As RAIDR results are potentially influenced by the steady-state levels of interest rates and deposit balances, they are less useful for comparisons across time periods. As shown in Table 3, banks pay lower retail deposit rates in the post-crisis period and the growth rate of deposit balances is also lower. To control for these inter-period differences, we propose a second metric: the h-month deposit rate elasticity, conditional on a structural shock for a particular bank:

$$\eta_h = \frac{Cumulative\ change\ in\ deposits\ over\ h\ months\ (in\ percent)}{Average\ change\ in\ deposit\ rate\ over\ h\ months\ (in\ percent)} \tag{13}$$

The conditional elasticity measures, relative to the *steady state*, how responsive the growth in deposits (measured in percent) is with respect to the average change in retail deposit rate (measured in percent) over a given time horizon. For example, $\eta_h = 1$ implies that when a shock hits now, an increase in the deposit rate of one percent from its steady state level, maintained over h months, leads to a one percent increase in the stock of deposits over and above the trend growth of deposits.

5.3 Results and discussion

This section summarises and discusses the results based on the two metrics outlined above. These are plotted in Figures 4 and 5. We report the highest and lowest values in the sample (denoted by dotted lines), and the average value weighted by individual bank's relative share of household deposits in the sample. Full sample results are represented by green lines; post-crisis sample results are in black. By comparing these two sets of results, we make *indirect inferences* about deposit behaviour in the UK *before* and *after* the financial crisis.

5.3.1 Idiosyncratic and aggregate deposit demand shocks

The top panel of Figure 4 displays RAIDR curves for both types of demand shocks. These curves are downward sloping for all banks in both data samples. In the post-crisis period, RAIDRs start at a level of 15 bps at $h = 3$, and fall to around 3 bps at $h = 12$. RAIDRs are lower across the horizon post-crisis, implying that banks find it relatively easier to raise retail deposits in response to deposit demand shocks in this period.

We also observe a steep, downward sloping RAIDR curve for idiosyncratic deposit demand shocks in the full-sample results (top left panel). One sample bank's RAIDR is unusually high at $h = 3$, taking a value in excess of 200 bps. We interpret this as banks being unable to mitigate the shock by using deposit rates to close the resulting deposit gap. Rather, these banks may have to resort to non-price mitigants, such as selling liquid assets, to cover these shocks.

In the post-crisis period, deposit responses are less different across banks, i.e. RAIDR curves are more closely clustered. This contrasts with the full-sample results, which show a much wider range of RAIDR values across all horizons, particularly for idiosyncratic deposit demand shocks.

The top panel of Figure 5 shows the dynamic conditional deposit elasticities conditional on two types of demand shocks. Values are generally smaller than one, implying that bank deposits are rate-inelastic. There has been an increase in elasticities for idiosyncratic demand shocks in the post-crisis sample, but elasticities for aggregate demand shocks are strikingly similar across both samples.

5.3.2 Idiosyncratic deposit supply shocks

The bottom left panel of Figure 4 shows that, when they face bank-specific deposit outflow shocks, banks have have to persistently impose a higher deposit rate rise in the full sample results but not in the post-crisis sample. We infer that there were challenges for banks to raise deposits in response to this type of shock *before the crisis*. This is consistent with our earlier comments on the impulse responses that show that banks struggle to generate positive deposit growth (top left panel of Figure 3).

Consistent with the RAIDR estimates, retail deposits conditional on this shock are found to be perfectly inelastic in the full sample (lower left panel of Figure 5). Deposit elasticities increase in the post-crisis sample, but are still very rate-inelastic as the weighted elasticity is just 0.12 for the 12-month horizon.

5.3.3 Aggregate deposit supply shocks

As presented in the lower right panel of Figure 4, RAIDR curves are not decreasing in the length of the horizon in the full-sample results, in particular there is a jump in the RAIDR at the 9-month horizon. In contrast, the RAIDR curves are strictly decreasing in the post-crisis sample results, and they are comparable to the RAIDR results with respect to deposit demand shocks. Conditional elasticities are also significantly larger in the post-crisis data (lower right panel of Figure 5).

However, we should point out one important caveat in the results: our model is likely to underestimate the difficulty banks face in retaining deposits in response to aggregate deposit supply shocks due to the absence of spill-over effects. It is not possible for all banks to close a deposit gap simultaneously. Through changing their deposit rates to attract deposits, banks effectively 'steal' deposits from elsewhere in the banking system: widening the deposit gap of other banks. This dynamic is likely to lead to other banks bidding up in response, making it difficult for banks to use deposit rates to attract net inflows of deposits.

5.3.4 Policy implications

The above estimates provide useful information for policy makers. First, in order to raise one billion pounds of retail deposits, banks face a median RAIDR in the order of 5 bps at the 12-month horizon, 10bps at the 6-month horizon, and 20 bps at the 3-month horizon, when we compare *post-crisis sample RAIDR estimates* across banks and shocks. In other words, the difference in RAIDR to close a deposit gap over a 3 month horizon compared to a 12 month horizon is around a factor of 4. This reflects the fact that deposits are typically difficult to raise quickly. This observation is further reinforced by the finding that deposits are rate-inelastic. For the post-crisis sample, the 12-month rate-elasticity ranges from around 0.1 to 0.5 across banks and shocks and typically takes a value around 0.3. This implies that a 1% increase in the deposit rate, maintained over 12 months, is associated with an increase in the stock of deposits, over and above the trend growth of deposits, of around 0.3% over the same horizon.

Second, to close a deposit gap equivalent to 1% of total deposits opened up by an idiosyncratic deposit demand shock, over a 12-month horizon, a bank must increase the rate on the stock of deposits by around 5 bps post-crisis (the median of weighted RAIDRs post-crisis). To put that in perspective, a bank with a deposit base of £50bn would incur an additional £0.25 bn per annum in interest expense. This provides one simple measure of the cost of a shock[21] and may be useful for assessing banks' resilience to shocks.

Third, evidence suggests that, although deposit rate-elasticity has increased in the post-crisis period, rate-elasticities with respect to deposit supply shocks are lower when compared to deposit demand shocks. Moreover, as discussed, our model may have under-estimated the true RAIDR conditional on aggregate deposit supply shocks because of the absence of spillover effects.

[21]In practice, banks have a range of options, including non-price options, available to them when trying to mitigate these shocks.

5.4 Robustness checks

We implement bank-by-bank and pooled-data estimation as robustness checks. We should note that pooling the data ignores bank-specific differences, whereas bank-by-bank estimation may produce biased estimates as the data sample is relatively short. Nevertheless, there is some merit in comparing them against our baseline results. The corresponding RAIDR curves are reported in Tables 4 and 5.

We generally see downward sloping RAIDR curves in the robustness checks exercises, especially for deposit demand shocks. It is still the case that deposits are less rate-elastic conditional on deposit supply shocks. Bank-by-bank results show that elasticities range widely, which is not surprising when there is no pooling across the short data sample. Overall, we are reassured that the baseline results are reasonably robust.

6 Historical decomposition

Historical decomposition is a useful technique for illustrating the historic paths of observed values of the endogenous variables in terms of the structural shocks and the path of the exogenous variables. This allows us to trace which of the structural shocks were driving movements in endogenous variables at different points in time. We can cross-check these descriptions with qualitative studies of key points in history as a means of validating the model's results.

In the interest of brevity, we only report results of the historical decomposition of two endogenous variables: retail deposit growth rates and the relative CDS of some banks in the *post-crisis* sample. The contributions of the structural shocks to the observed data series are represented by coloured bars. By definition, the sum of the heights of the coloured bars equates to the value of the observed data. To preserve confidentiality and anonymity, neither the observed data series nor the y-axis labels are plotted.

6.1 Retail deposit growth

Figures 6 and 7 display the historical decomposition of retail deposit growth rates of two anonymous banks, which we call bank A and bank B. We observe that:

- In 2008Q3, aggregate deposit supply shocks largely explain the fall in deposit growth for both banks. The model apparently captures a deposit flight that affected banks (modelled by the model parameter φ), indicating that a flight-to-cash may have occurred at the onset of the global financial crisis.

- For bank A, aggregate deposit demand shocks play a key role in explaining the change in retail deposits between 2009 and 2013. For most of the quarters since 2010, the increase in deposit flow is explained by positive aggregate deposit demand shocks. This likely is explained by this bank substituting away from non-deposit funding (wholesale funding) sources.

- The increase in retail deposit flow experienced by bank B between 2009 and 2010, and especially the sharp increase in 2009Q2-3 and 2010Q4, is largely explained by aggregate deposit demand shock. We take this as evidence that bank B was competing harder for deposits because it was finding it increasingly difficult to raise alternative sources of funding such as wholesale funding. Interestingly, this trend is reversed after 2011, in contrast to Bank A.

6.2 Relative CDS

Figures 8 and 9 illustrate the historical decomposition for the relative CDS spreads of two anonymous banks, bank X and bank Y.

- Bank X's CDS spread rises relative to the other UK banks in 2008 and early 2009. This can be largely explained by positive idiosyncratic deposit demand shocks (caused by adverse idiosyncratic wholesale funding conditions), and to some extent, aggregate deposit supply shocks. The main driving forces behind the fall in its CDS spread over the course of 2010 and 2012 are negative idiosyncratic deposit demand shocks, i.e. improving bank-specific wholesale funding conditions.

- In contrast, idiosyncratic deposit supply shocks play an important role in explaining the rise in the relative CDS spreads of bank Y, especially in the period of 2009 and 2012. Similarly, the subsequent decline in relative CDS spreads after 2012 is largely attributable to this shock. This likely suggests that households lost confidence in this bank (relative to the other UK banks) following the financial crisis.

7 Conclusion and future work

We have presented a quantitative study on retail deposit behaviour at major banks in the UK. We take advantage of a confidential dataset of deposit rates and balances for four UK banks, that starts in January 2004. Having estimated a panel of BVARs with hierarchical priors, we uncover deposit demand and supply shocks, both to individual banks and in aggregate, from micro-founded sign restrictions derived from a stylised partial equilibrium model. Based on the impulse response functions, we develop two metrics to estimate the cost for banks to close deposit gaps opened up following cyclical shocks. To account for the possible structural break in the deposit market behaviours during the financial crisis, we carry out split-sample analysis. We report and compare the results for the 'full-sample' and 'post-crisis' periods, highlighting the fact that differences may provide (indirect) empirical support for a possible structural change in household deposit behaviour in the wake of the financial crisis.

We present some new and interesting empirical results. Our estimates show that when banks are able to cover their deposit gap with less urgency, they are able to raise their deposit rates by less than when they are forced to cover the gap over a shorter horizon. UK retail deposits are also shown to be rate-inelastic. Our post-crisis sample estimates show that elasticities lie at the range of 0.1 to 0.5 at the 12-month horizon. Moreover, our results show that elasticities conditional on deposits demand shocks are larger than those conditional on deposit supply shocks, suggesting that banks are more vulnerable to deposit supply shocks.

We recognise that there is scope for further work on this topic. In particular, our modelling framework could be enhanced in a number of ways. One area for future work is the introduction of non-linearities, including non-linear funding costs, spill-over effects or even bank defaults, to our theoretical and empirical models. Another avenue to explore is the relaxation of the restrictive assumptions made when modelling banks' balance sheets. For example, banks could be allowed to accumulate liquid assets which can be easily converted to cash when they face funding shortfalls. We leave these extensions to future research.

Appendix

Proof of Proposition 2

By chain rule, we rewrite

$$\frac{\partial D}{\partial \psi_i} = \frac{\partial D}{\partial \overline{r}} \frac{\partial \overline{r}}{\partial \psi_i} = 0$$

Since the equilibrium aggregate deposit is not a function of $\overline{r}$ as shown in equation (4), implying that $\frac{\partial D}{\partial \overline{r}} = 0$, results follow.

Proof of Proposition 3

Note that $\frac{\partial \widetilde{s}_i}{\partial z} = \frac{\partial}{\partial z}(s_i - s) = \phi - \int_0^1 \phi di = 0$.

For a change in σ_i^b of bank i, $s_i'\left(\sigma_i^b\right) > 0$ but $s_j'\left(\sigma_i^b\right) = 0$, $\forall j \neq i$. The market average spread s will move less than one-for-one compared with the individual bank spread s_i. Therefore $\frac{\partial \widetilde{s}_i}{\partial \sigma_i^b} = \frac{\partial}{\partial \sigma_i^b}(s_i - s) = s_i'\left(\sigma_i^b\right) - \int_0^1 s_j'\left(\sigma_j^b\right) dj > 0$.

Proof of Proposition 4

Considering the equilibrium deposit demand (10), and the equilibrium supply of aggregate deposit (4), as well as the following two equations derived from the equilibrium supply of deposits to an individual bank i(6):

$$r_i\left(D_i\right) = \psi_i \overline{r} \left(\frac{D_i}{D}\right)^{\frac{1}{\eta}}$$

$$\frac{\partial r_i\left(D_i\right)}{\partial D_i} = \frac{\psi_i \overline{r}}{\eta D} \left(\frac{D_i}{D}\right)^{\frac{1}{\eta}-1}$$

we obtain the equilibrium condition

$$\psi_i \overline{r} \left(1 + \frac{1}{\eta}\right) \left[\frac{D_i}{(1-\varphi) w \left(1 - \frac{\sigma_p}{\sigma_r}\right)}\right]^{\frac{1}{\eta}} + C_i'\left(D_i\right) = \widetilde{r} + s_i\left(z, \sigma_i^b\right) \tag{14}$$

This is a non-linear equation in D_i. Define $\Delta = 1 - \frac{\sigma_p}{\sigma_r} > 0$, and recall our assumption that $C_i''\left(D_i\right) > 0$ and $s_i'\left(\sigma_i^b\right) > 0$. By implicit function theorem, we derive the following derivatives

$$\frac{\partial D_i}{\partial \sigma_i^b} = \frac{s_i'\left(\sigma_i^b\right)}{\psi_i \overline{r}\left(1 + \frac{1}{\eta}\right) \frac{1}{\eta D} \left(\frac{D_i}{D}\right)^{\frac{1}{\eta}-1} + C_i''\left(D_i\right)} > 0$$

$$\frac{\partial D_i}{\partial z} = \frac{1}{\psi_i \overline{r}\left(1+\frac{1}{\eta}\right)\frac{1}{\eta D}\left(\frac{D_i}{D}\right)^{\frac{1}{\eta}-1} + C_i''\left(D_i\right)} > 0$$

$$\frac{\partial D_i}{\partial \psi_i} = \frac{-\overline{r}\left(1+\frac{1}{\eta}\right)\left(\frac{D_i}{\Delta}\right)^{\frac{1}{\eta}}}{\psi_i \overline{r}\left(1+\frac{1}{\eta}\right)\frac{1}{\eta D}\left(\frac{D_i}{D}\right)^{\frac{1}{\eta}-1} + C_i''\left(D_i\right)} < 0$$

$$\frac{\partial D_i}{\partial \sigma_p} = \frac{\overline{r}\psi_i\left(1+\frac{1}{\eta}\right)\frac{1}{\eta}\frac{D_i}{w\Delta^2}\left(\frac{D_i}{\Delta}\right)^{\frac{1}{\eta}-1}\frac{1}{\sigma_r^2}}{\psi_i \overline{r}\left(1+\frac{1}{\eta}\right)\frac{1}{\eta D}\left(\frac{D_i}{D}\right)^{\frac{1}{\eta}-1} + C_i''\left(D_i\right)} < 0$$

$$\frac{\partial D_i}{\partial \varphi} = \frac{\overline{r}\psi_i\left(1+\frac{1}{\eta}\right)\frac{1}{\eta}\frac{D_i}{w\Delta}\left(\frac{D_i}{\Delta}\right)^{\frac{1}{\eta}-1}\frac{1}{(1-\varphi)^2}}{\psi_i \overline{r}\left(1+\frac{1}{\eta}\right)\frac{1}{\eta D}\left(\frac{D_i}{D}\right)^{\frac{1}{\eta}-1} + C_i''\left(D_i\right)} < 0$$

Proof of Proposition 5

Similarly, by plugging (6) into (14), we can solve for the equilibrium deposit rate:

$$\begin{aligned}
\psi_i \overline{r}\left(1+\frac{1}{\eta}\right)\left[\frac{D_i}{D}\right]^{\frac{1}{\eta}} + C_i'\left(D_i\right) &= \widetilde{r} + s_i\left(z, \sigma_i^b\right) \\
\left(1+\frac{1}{\eta}\right) r_i + C_i'\left(\left(\frac{r_i/\psi_i}{\overline{r}}\right)^{\eta}(1-\varphi)\, w\left(1-\frac{\sigma_p}{\sigma_r}\right)\right) &= \widetilde{r} + s_i\left(z, \sigma_i^b\right)
\end{aligned}$$

which is also a non-linear equation in r_i. Again by implicit function theorem, we derive the relevant derivatives:

$$\frac{\partial r_i}{\partial \sigma_i^b} = \frac{s_i'\left(\sigma_i^b\right)}{1+\frac{1}{\eta} + C_i''\left(D_i\right)\frac{\eta(1-\varphi)w}{\psi_i \overline{r}}\left(\frac{r_i/\psi_i}{\overline{r}}\right)^{\eta-1}\left(1-\frac{\sigma_p}{\sigma_r}\right)} > 0$$

$$\frac{\partial r_i}{\partial z} = \frac{1}{1+\frac{1}{\eta} + C_i''\left(D_i\right)\frac{\eta(1-\varphi)w}{\psi_i \overline{r}}\left(\frac{r_i/\psi_i}{\overline{r}}\right)^{\eta-1}\left(1-\frac{\sigma_p}{\sigma_r}\right)} > 0$$

$$\frac{\partial r_i}{\partial \psi_i} = \frac{s_i'\left(\psi_i\right) + C_i''\left(D_i\right)(1-\varphi)\, w\eta\left(1-\frac{\sigma_p}{\sigma_r}\right)\frac{r_i}{\psi_i^2 \overline{r}}\left(\frac{r_i}{\psi_i \overline{r}}\right)^{\eta-1}}{1+\frac{1}{\eta} + C_i''\left(D_i\right)\frac{\eta(1-\varphi)w}{\psi_i \overline{r}}\left(\frac{r_i/\psi_i}{\overline{r}}\right)^{\eta-1}\left(1-\frac{\sigma_p}{\sigma_r}\right)} > 0$$

$$\frac{\partial r_i}{\partial \sigma_p} = \frac{C_i''\left(D_i\right)\frac{(1-\varphi)w\left(1-\frac{\sigma_p}{\sigma_r}\right)}{\sigma_r^2}\left(\frac{r_i/\psi_i}{\overline{r}}\right)^{\eta}}{1+\frac{1}{\eta} + C_i''\left(D_i\right)\frac{\eta(1-\varphi)w}{\psi_i \overline{r}}\left(\frac{r_i/\psi_i}{\overline{r}}\right)^{\eta-1}\left(1-\frac{\sigma_p}{\sigma_r}\right)} > 0$$

$$\frac{\partial r_i}{\partial \varphi} = \frac{C_i''\left(D_i\right)\frac{w\left(1-\frac{\sigma_p}{\sigma_r}\right)}{\sigma_r^2}\left(\frac{r_i/\psi_i}{\bar{r}}\right)^{\eta}}{1+\frac{1}{\eta}+C_i''\left(D_i\right)\frac{\eta(1-\varphi)w}{\psi_i\bar{r}}\left(\frac{r_i/\psi_i}{\bar{r}}\right)^{\eta-1}\left(1-\frac{\sigma_p}{\sigma_r}\right)} > 0$$

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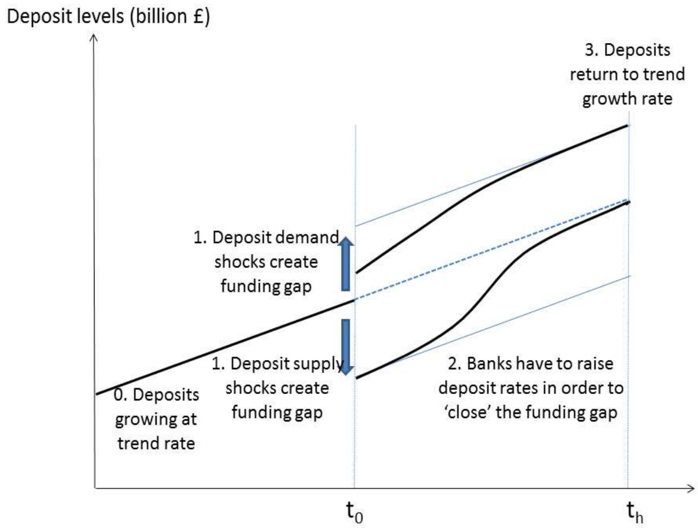

Figure 1a: A stylised dynamic for household deposits in *level*.

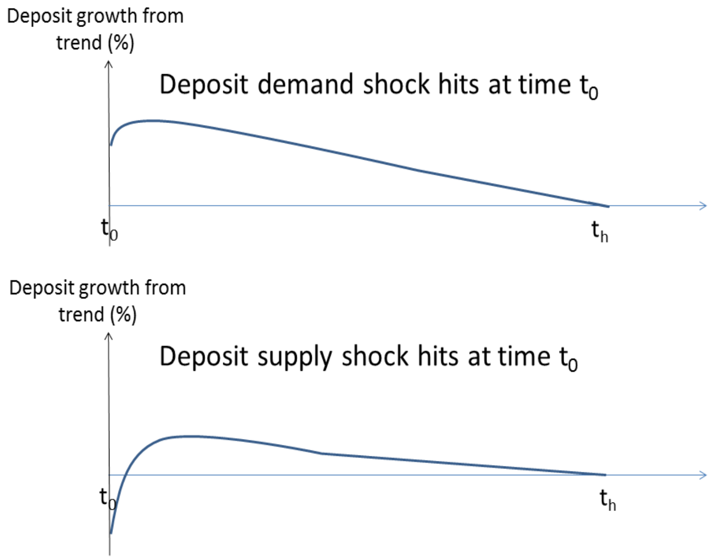

Figure 1b: Intuitive impulse responses of the deposit *growth* corresponding to a funding shortfall caused by deposit demand and supply shocks, corresponding to the descriptions in Figure 1a.

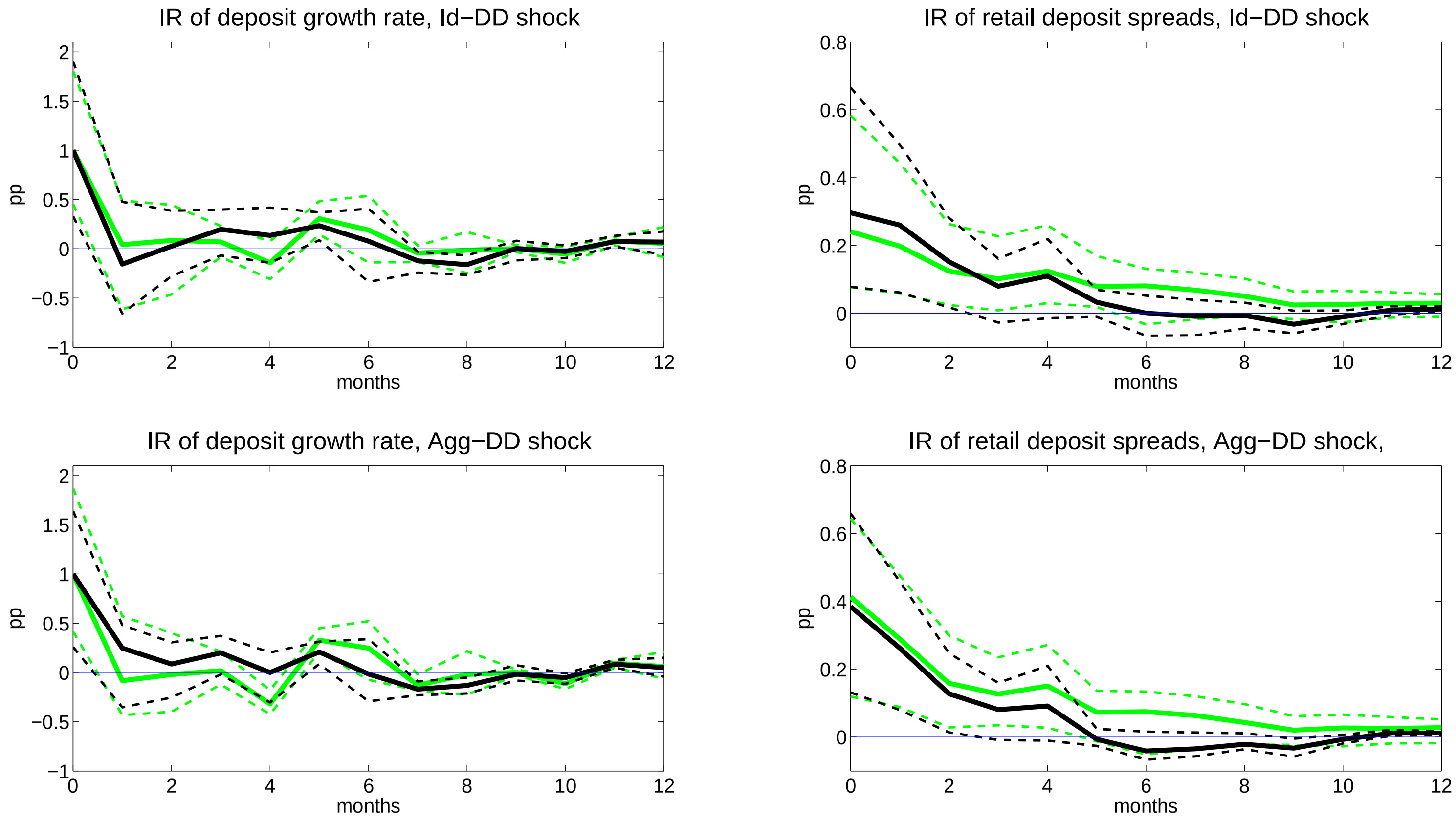

Figure 2: Impulse responses of deposit growth rates (left panel) and retail deposit spreads (right panel) of an anonymous bank in the estimation. The responses are conditional on idiosyncratic deposit demand shocks (top panel) and aggregate deposit demand shocks (bottom panel). Black lines represent the results for the 'post-crisis sample' data, whereas green lines represents the results for the 'full sample' data. Solid lines correpond to the median impulse responses, and dotted lines to the 16th and 84th percentile of the responses.

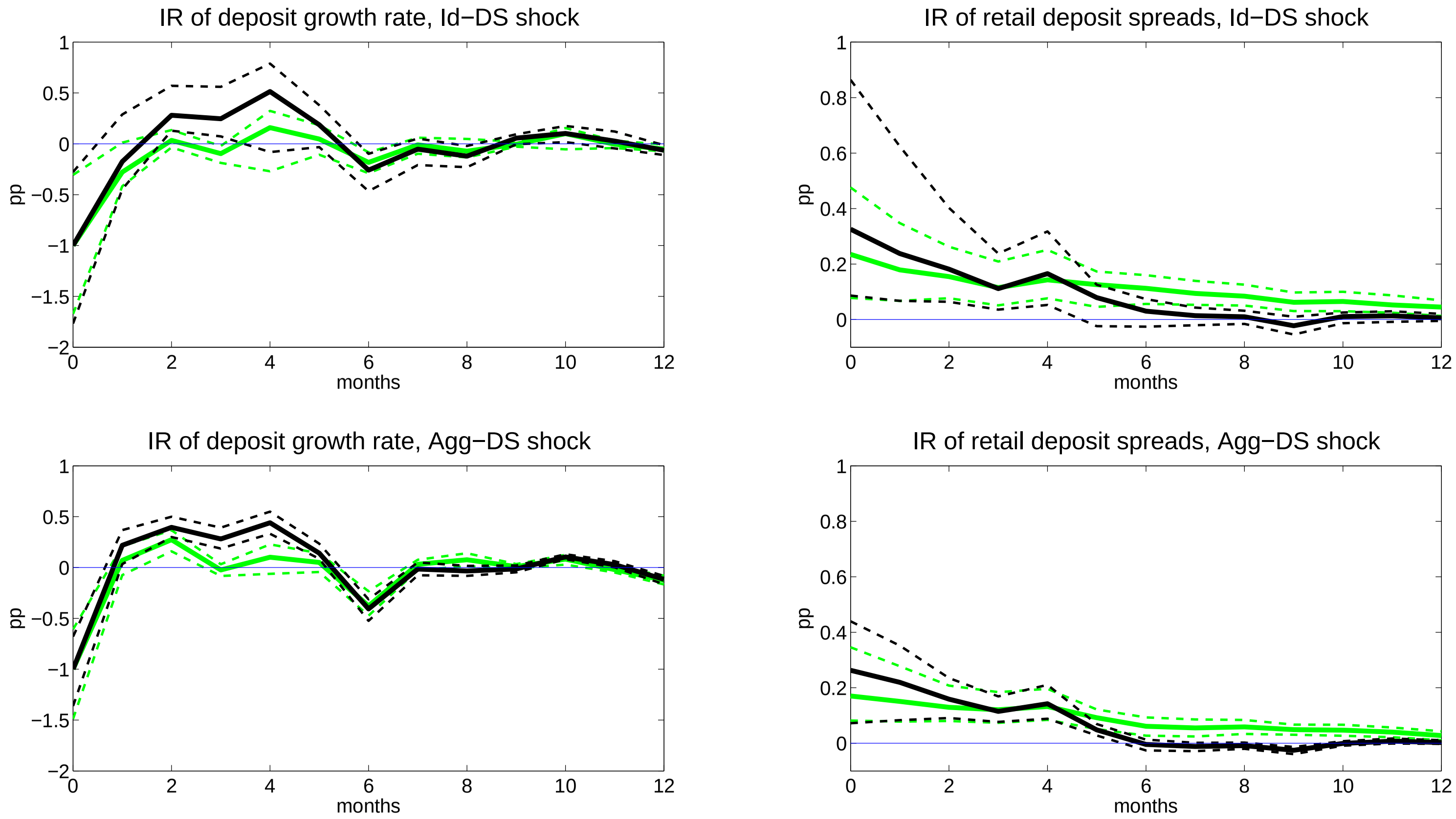

Figure 3: Impulse responses of deposit growth rates (left panel) and retail deposit spreads (right panel) of an anonymous bank in the estimation. The responses are conditional on idiosyncratic deposit supply shocks (top panel) and aggregate supply demand shocks (bottom panel). Black lines represent the results for the 'post-crisis sample' data, whereas green lines represents the results for the 'full sample' data. Solid lines correpond to the median impulse responses, and dotted lines to the 16th and 84th percentile of the responses.

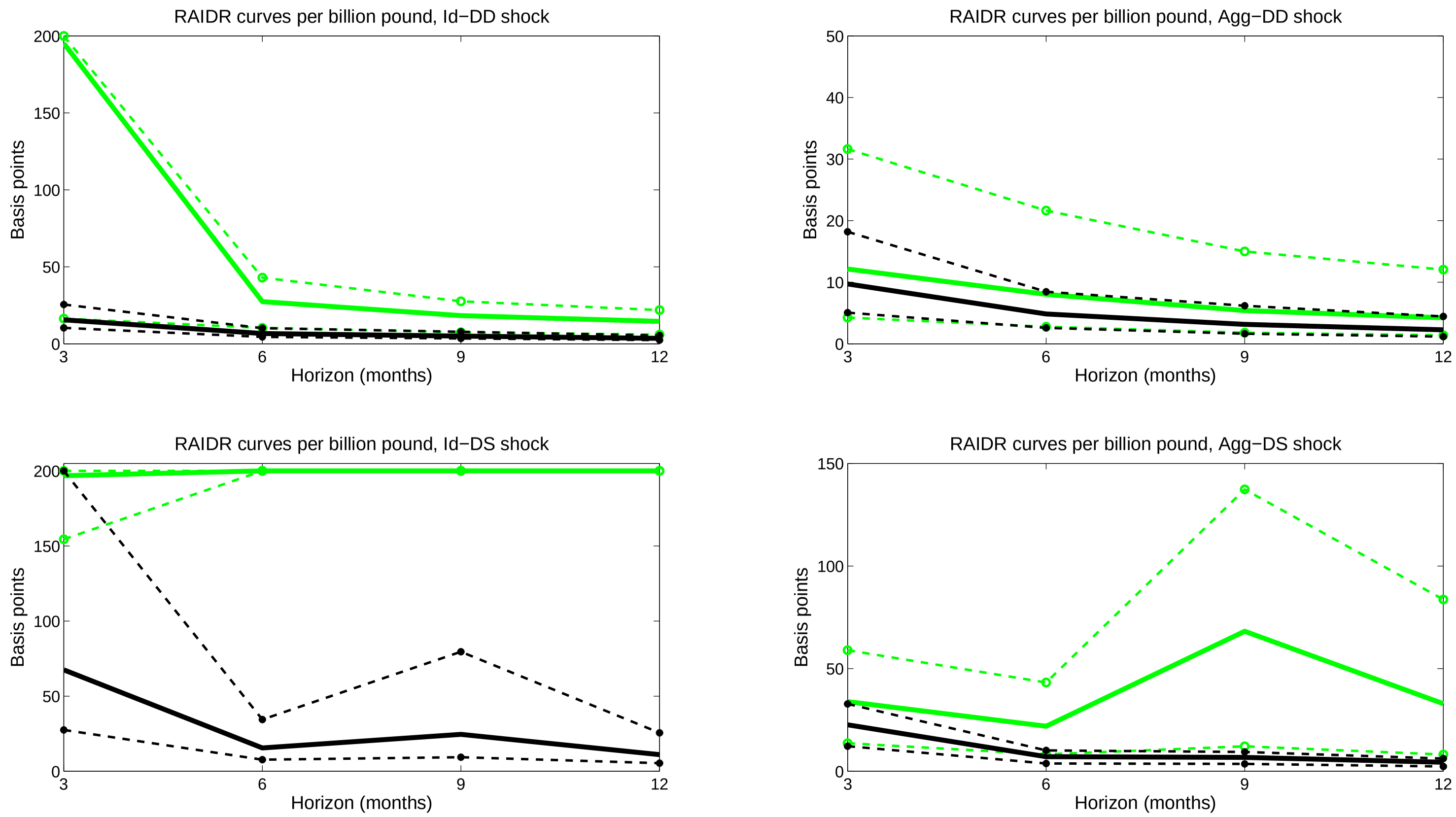

Figure 4: RAIDR curves per billion pound, conditional on the four identified structural shocks. Green lines denote the 'full-sample' results, whereas black lines denote the 'post-crisis' results. Computed by transforming the impulse reponses to RAIDRs for each bank in the sample. Bold lines show the average RAIDR *weighted by each bank's market share of household retail deposits*, whereas dotted lines show the highest and lowest RAIDR values.

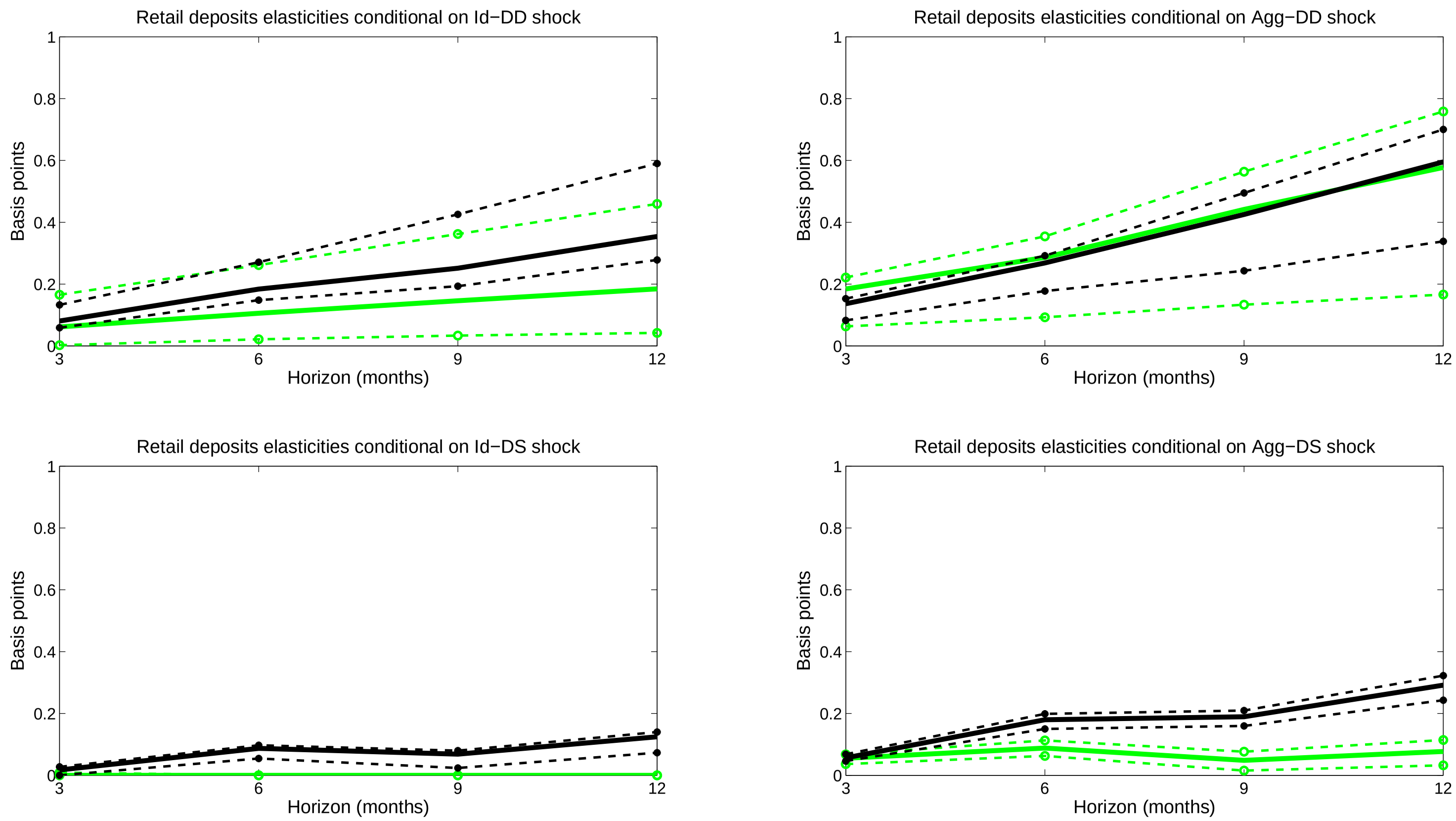

Figure 5: Household dynamic retail deposits elasticities conditional on the four identified structural shocks. Green lines denote the 'full-sample' results, whereas black lines denote the 'post-crisis' results. Bold lines show the average elasticity values *weighted by each bank's market share of retail deposits*, whereas dotted lines show the highest and lowest elasticity values.

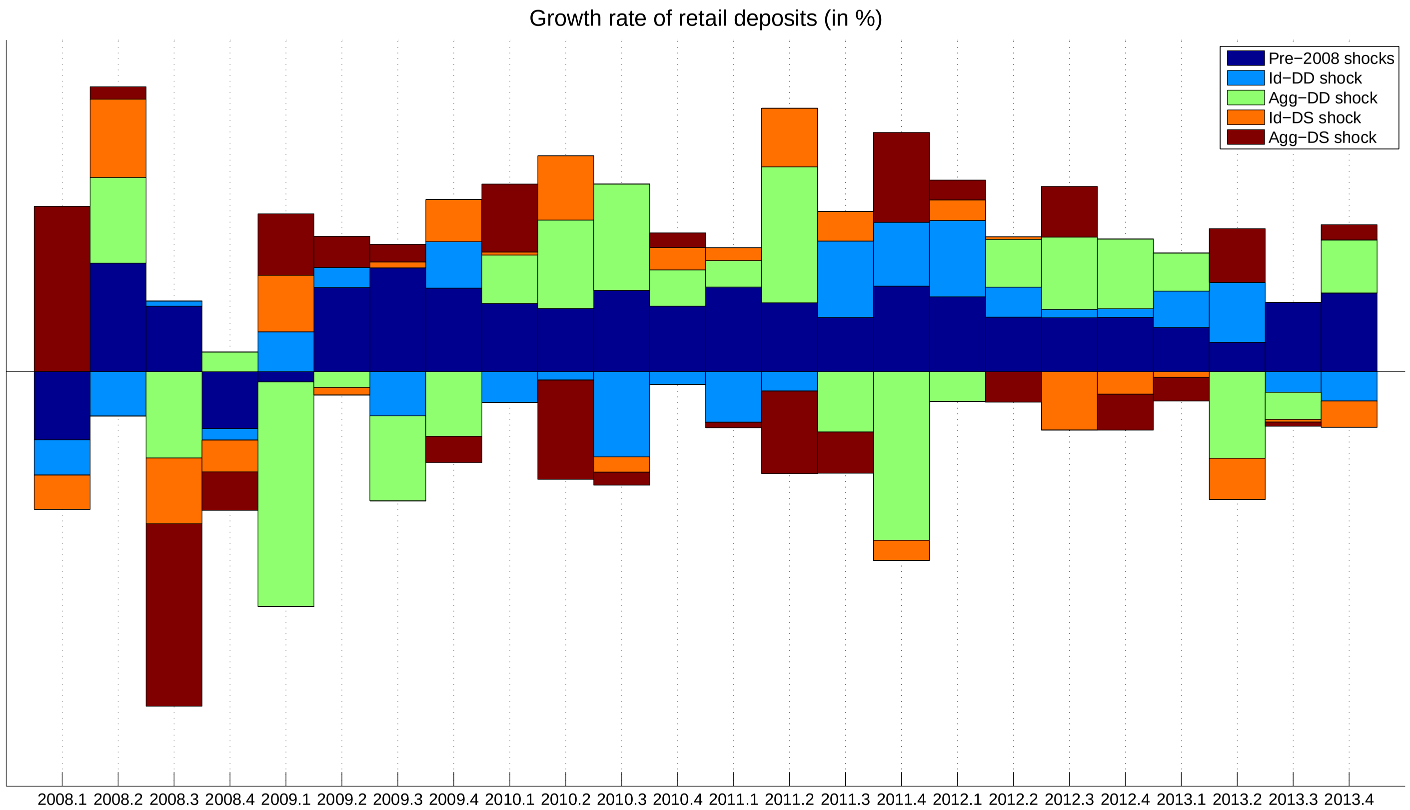

Figure 6: Historical decomposition for retail deposit changes for an anonymous bank 'A' in the *post-crisis* sample. The actual data series and the y-axis labels are hidden to preserve confidentiality and anonymity. Variations not explained by the four structural shocks are denoted as 'Pre-2008 shocks'.

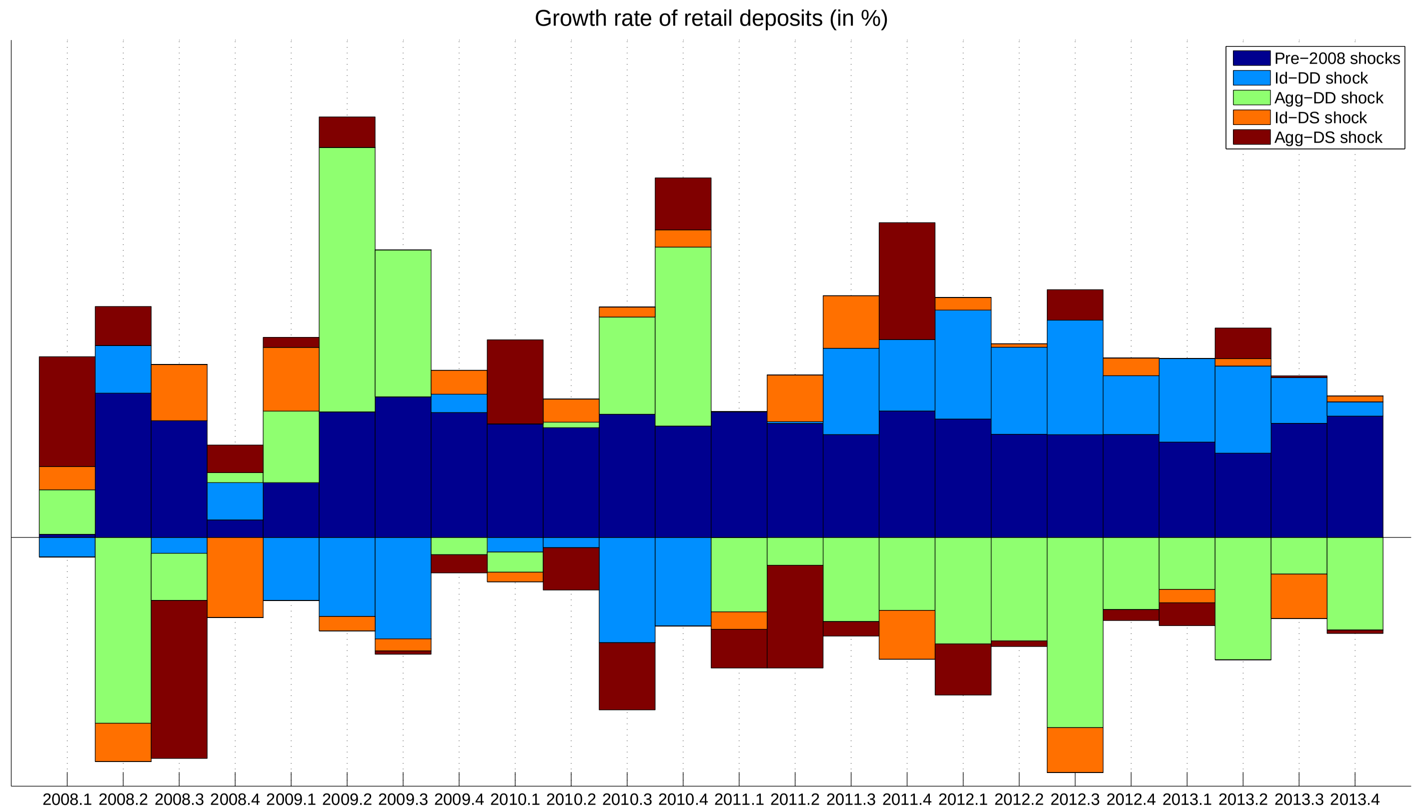

Figure 7: Historical decomposition for retail deposit changes for an anonymous bank 'B' in the *post-crisis* sample. The actual data series and the y-axis labels are hidden to preserve confidentiality and anonymity. Variations not explained by the four structural shocks are denoted as 'Pre-2008 shocks'.

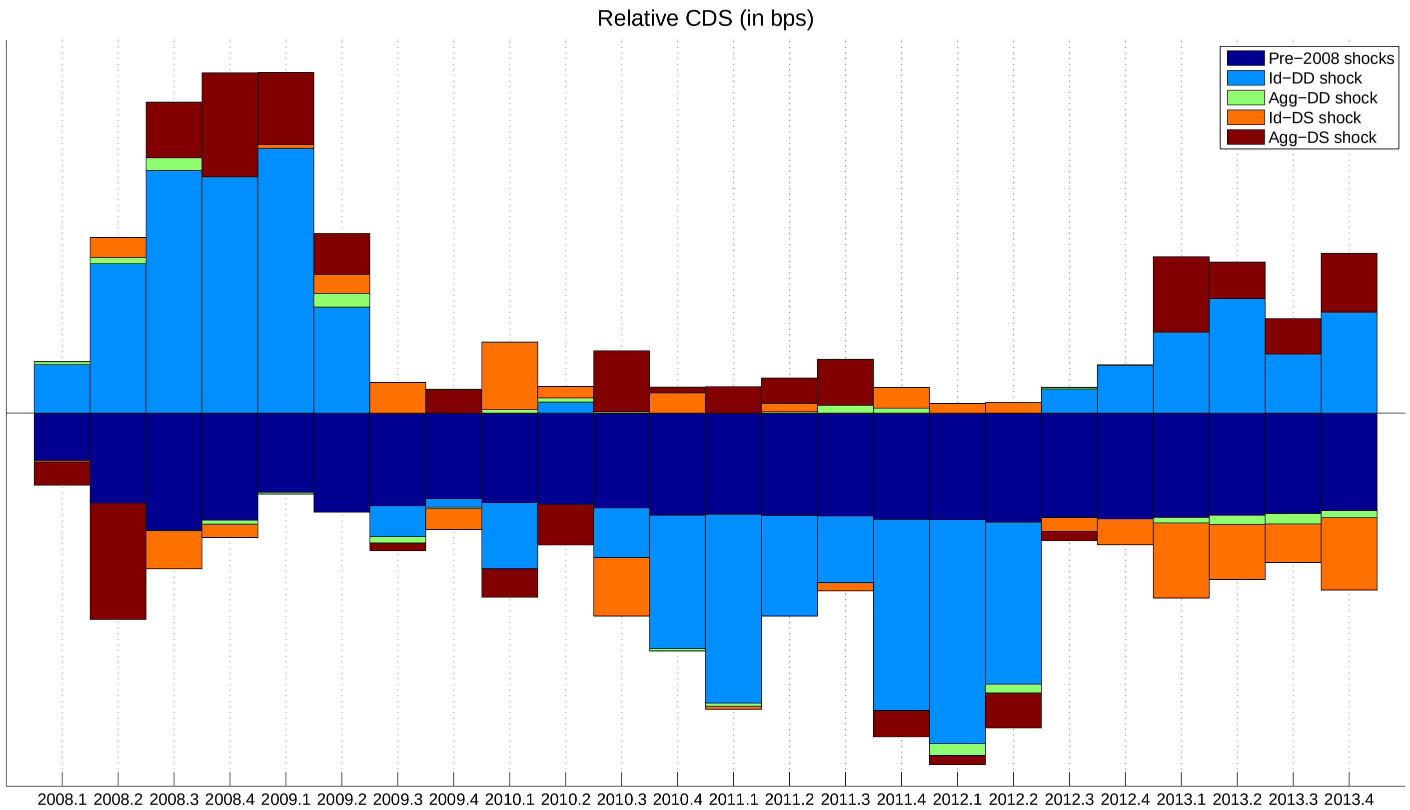

Figure 8: Historical decomposition for the relative CDS spreads for an anonymous bank 'X' in the *post-crisis* sample. The actual data series and the y-axis labels are hidden to preserve confidentiality and anonymity. Variations not explained by the four structural shocks are denoted as 'Pre-2008 shocks'.

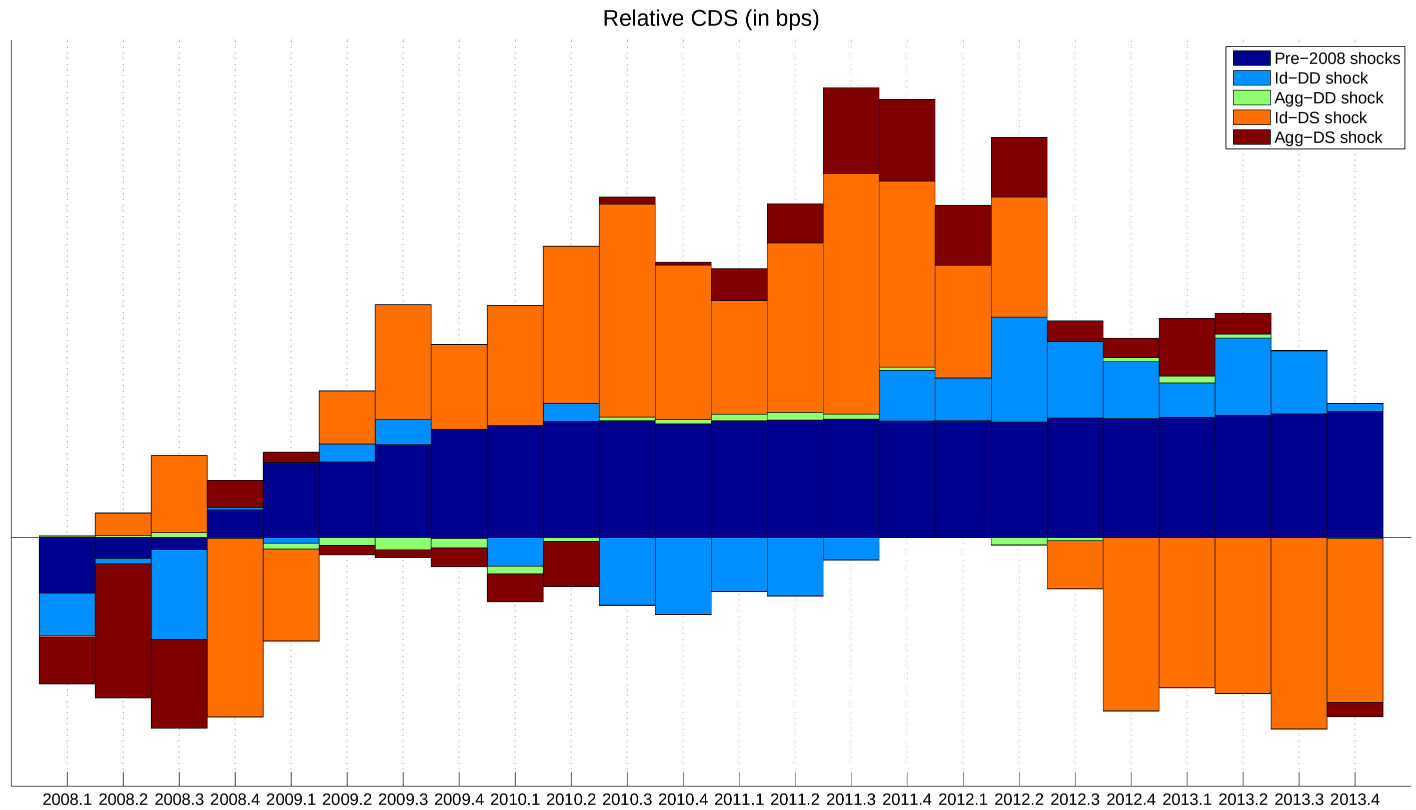

Figure 9: Historical decomposition for the relative CDS spreads for an anonymous bank 'Y' in the *post-crisis* sample. The actual data series and the y-axis labels are hidden to preserve confidentiality and anonymity. Variations not explained by the four structural shocks are denoted as 'Pre-2008 shocks'.

Table 4: Weighted required average increase in retail deposit rate (RAIDR, in bps) for banks to raise 1 billion pound of retail deposits within h months, conditional on each structural shock: baseline and robustness checks results.

	Full sample				Post-crisis sample			
	h=3	h=6	h=9	h=12	h=3	h=6	h=9	h=12
(i) Idiosyncratic deposit demand shocks								
Baseline (W)	195	27.4	18.3	14.5	15.5	6.65	4.95	3.50
Bank-by-bank (W)	47.5	42.1	40.9	40.1	8.87	3.30	2.43	1.92
Pooled	87.7	62.4	33.2	29.6	51.1	29.0	16.4	13.6
(ii) Aggregate deposit demand shocks								
Baseline (W)	12.1	8.03	5.38	4.22	9.72	4.84	3.16	2.26
Bank-by-bank (W)	6.00	3.80	1.55	1.44	7.05	3.10	2.47	2.29
Pooled	9.78	4.17	2.39	1.74	9.79	3.89	2.20	1.82
(iii) Idiosyncratic deposit supply shocks								
Baseline (W)	118	>200	>200	>200	67.5	15.5	24.6	11.0
Bank-by-bank (W)	134	>200	>200	>200	125	101	112	105
Pooled	>200	>200	>200	>200	>200	>200	>200	>200
(iv) Aggregate deposit supply shocks								
Baseline (W)	33.9	21.9	68.2	32.9	22.6	7.08	6.71	4.37
Bank-by-bank (W)	124	15.8	162	173	101	96	139	135
Pooled	81.3	28.0	>200	>200	>200	15.7	47.2	16.8

Note: Values '>200' indicate that banks may need to impose a very high rate rise in order to cover the funding shortfall, subject to our modelling and estimation assumptions. (W) indicates results weighted by the relative share of retail deposit size of the banks. 'Baseline' refers to the results obtained by the panel of BVARs; 'Bank-by-bank' indicates results estimated without any form of pooling; 'Pooled' means that results are obtained with pooling data across all banks.

Table 5: Weighted dynamic rate-elasticities conditional on each structural shock: baseline and robustness checks results.

	Full sample				**Post-crisis sample**			
	h=3	h=6	h=9	h=12	h=3	h=6	h=9	h=12
(i) Idiosyncratic deposit demand shocks								
Baseline (W)	0.02	0.11	0.15	0.18	0.08	0.18	0.25	0.35
Bank-by-bank (W)	0.09	0.08	0.07	0.05	0.16	1.00	1.33	0.96
Pooled	0.03	0.04	0.08	0.09	0.04	0.06	0.11	0.14
(ii) Aggregate deposit demand shocks								
Baseline (W)	0.18	0.29	0.44	0.58	0.14	0.27	0.43	0.60
Bank-by-bank (W)	0.65	1.27	>2	>2	0.19	0.77	0.70	0.75
Pooled	0.28	0.65	1.13	1.56	0.19	0.48	0.85	1.03
(iii) Idiosyncratic deposit supply shocks								
Baseline (W)	0	0	0	0	0.02	0.09	0.07	0.12
Bank-by-bank (W)	0.01	0.02	0	0	0.03	0.11	0.02	0.07
Pooled	0	0	0	0	0	0	0	0
(iv) Aggregate deposit supply shocks								
Baseline (W)	0.06	0.09	0.05	0.08	0.06	0.18	0.19	0.29
Bank-by-bank (W)	0.02	0.11	0.02	0.02	0.08	0.08	0.03	0.03
Pooled	0.03	0.10	0	0	0.01	0.12	0.04	0.11

Note: Values '0' indicate very rate-inelastic deposits behaviour, whereas '>2' indicates very rate-elastic ones, subject to our modelling and estimation assumptions. (W) indicates results weighted by the relative share of retail deposit size of the banks. 'Baseline' refers to the results obtained by the panel of BVARs; 'Bank-by-bank' indicates results estimated without any form of pooling; 'Pooled' means that results are obtained with pooling data across all banks.

Separate Chart Appendix to

The rate elasticity of retail deposits in the United Kingdom: a macroeconomic investigation

July 20, 2015

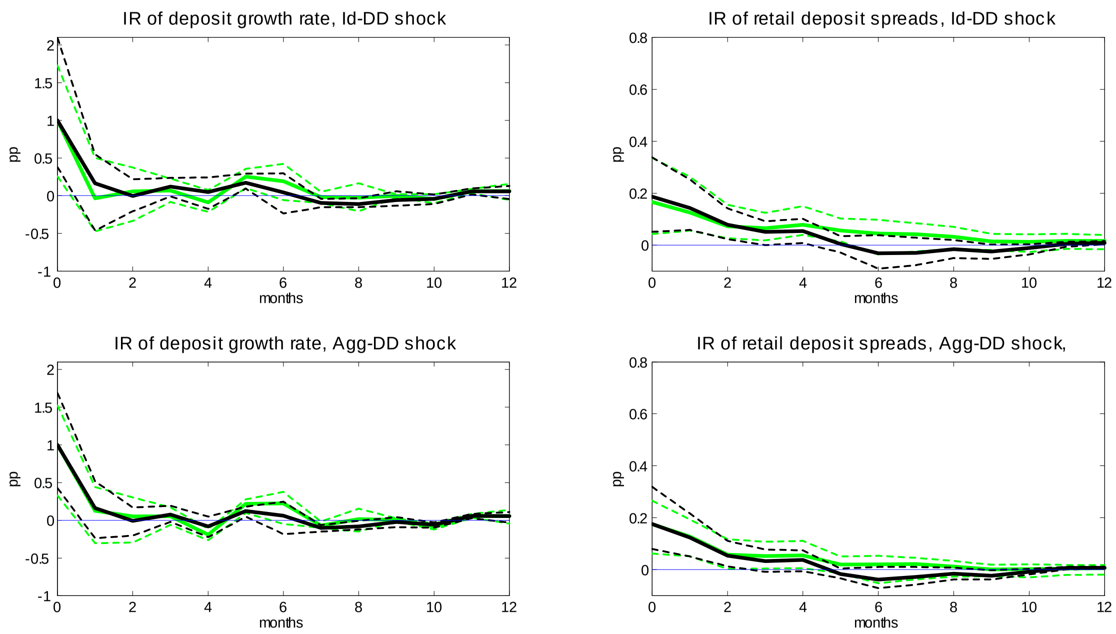

Figure 1: Impulse responses of deposit growth rates (left panel) and retail deposit spreads (right panel) of an anonymous bank 2 in the estimation. The responses are conditional on idiosyncratic deposit demand shocks (top panel) and aggregate deposit demand shocks (bottom panel). Black lines represent the results from 'post-crisis sample' data, whereas green lines represents the results from 'full sample' data. Solid lines correpond to the median impulse responses, and dotted lines to the 16th and 84th percentile of the responses.

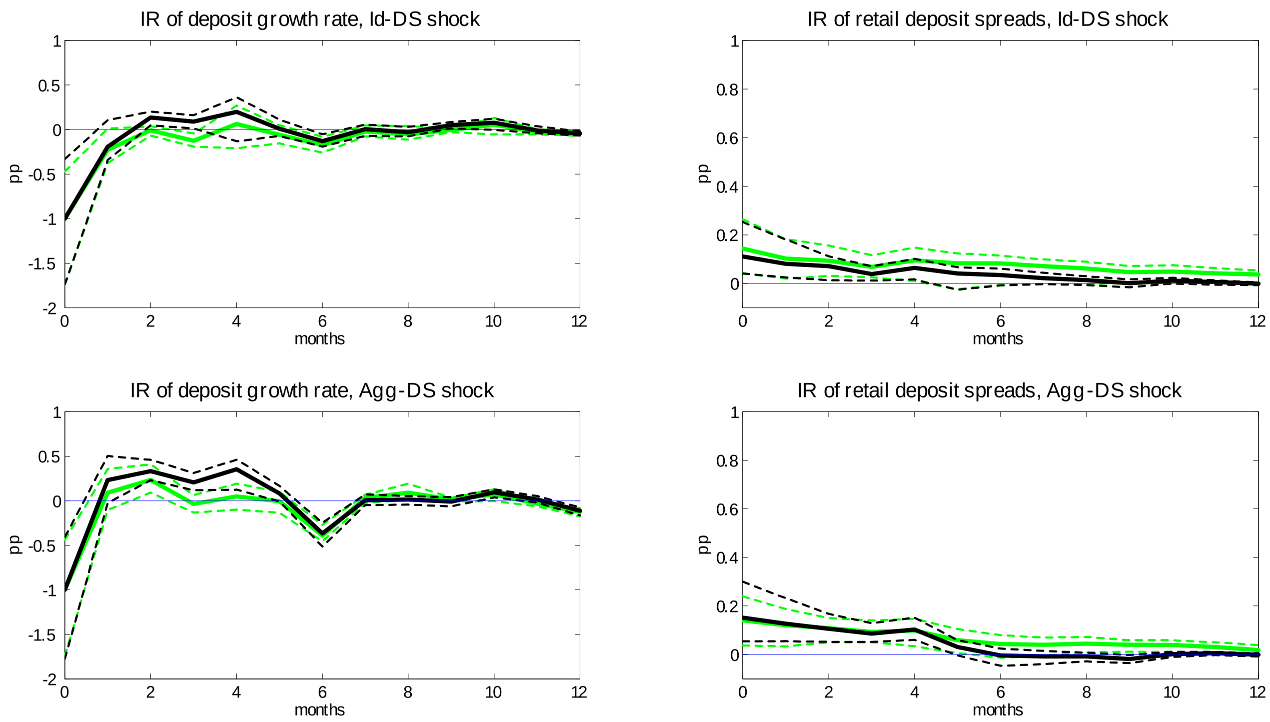

Figure 2: Impulse responses of deposit growth rates (left panel) and retail deposit spreads (right panel) of an anonymous bank 2 in the estimation. The responses are conditional on idiosyncratic deposit supply shocks (top panel) and aggregate supply demand shocks (bottom panel). Black lines represent the results from 'post-crisis sample' data, whereas green lines represents the results from 'full sample' data. Solid lines correpond to the median impulse responses, and dotted lines to the 16th and 84th percentile of the responses.

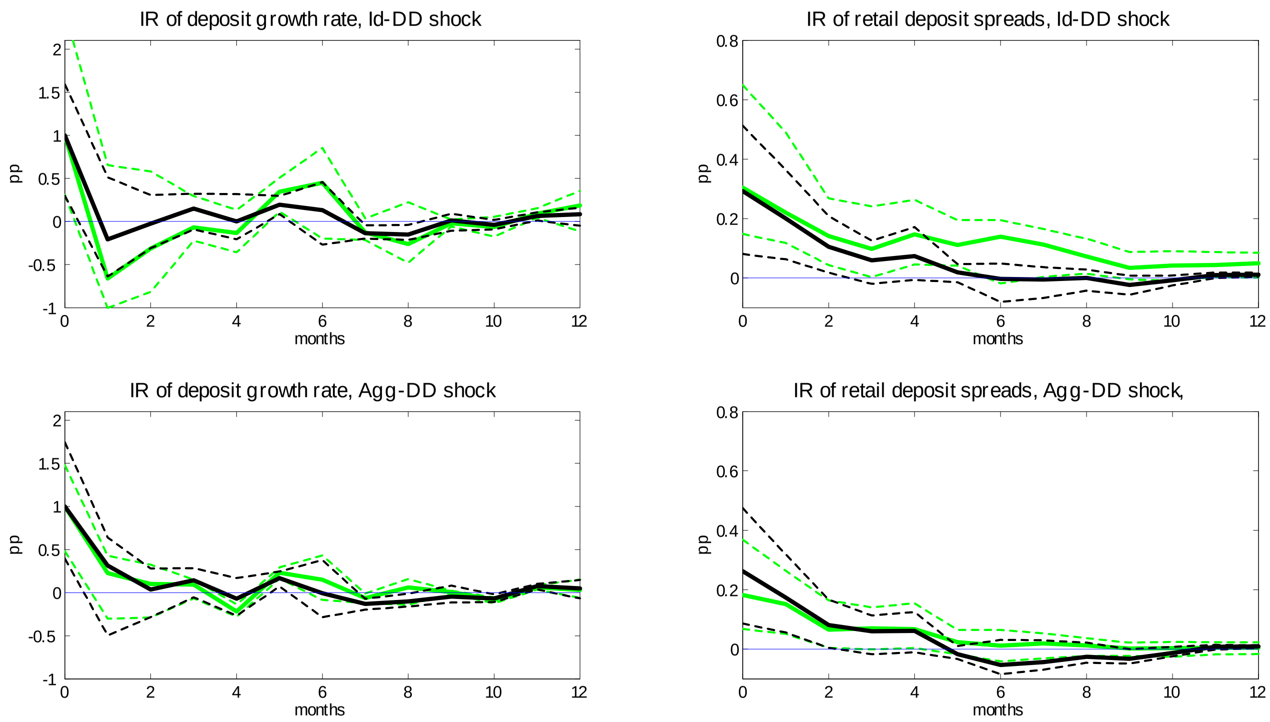

Figure 3: Impulse responses of deposit growth rates (left panel) and retail deposit spreads (right panel) of an anonymous bank 3 in the estimation. The responses are conditional on idiosyncratic deposit demand shocks (top panel) and aggregate deposit demand shocks (bottom panel). Black lines represent the results from 'post-crisis sample' data, whereas green lines represents the results from 'full sample' data. Solid lines correpond to the median impulse responses, and dotted lines to the 16th and 84th percentile of the responses.

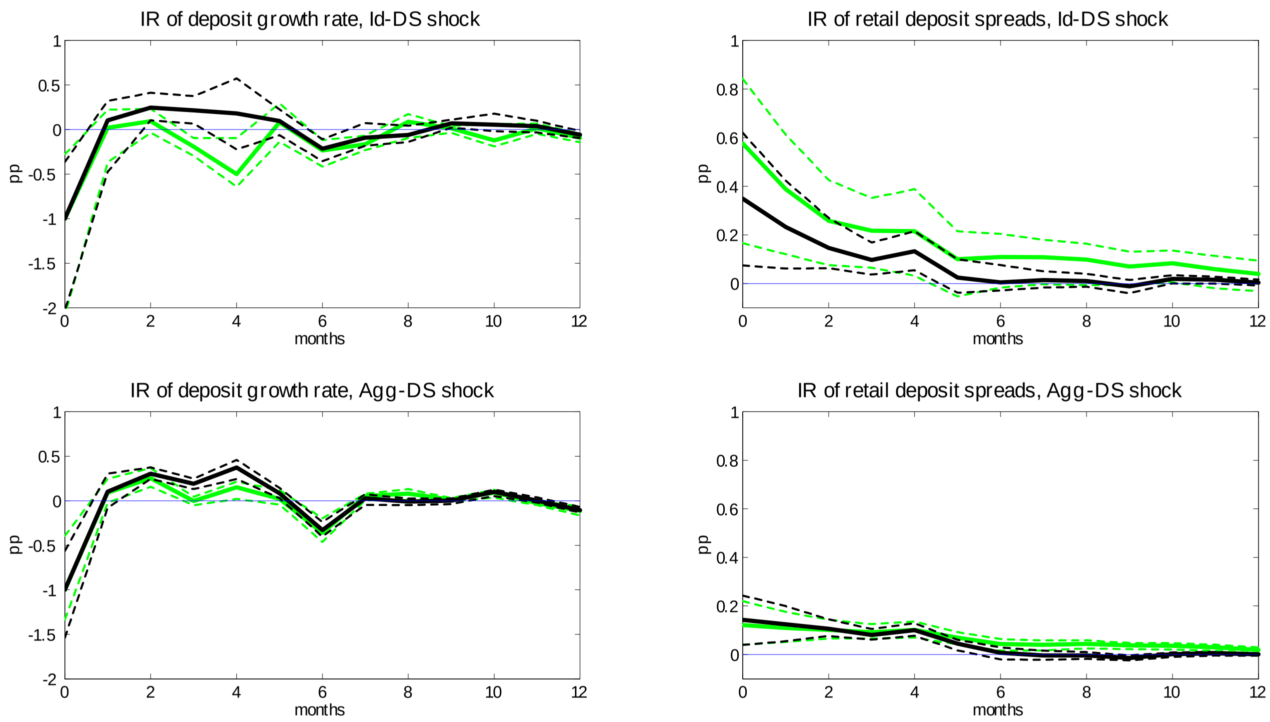

Figure 4: Impulse responses of deposit growth rates (left panel) and retail deposit spreads (right panel) of an anonymous bank 3 in the estimation. The responses are conditional on idiosyncratic deposit supply shocks (top panel) and aggregate supply demand shocks (bottom panel). Black lines represent the results from 'post-crisis sample' data, whereas green lines represents the results from 'full sample' data. Solid lines correpond to the median impulse responses, and dotted lines to the 16th and 84th percentile of the responses.

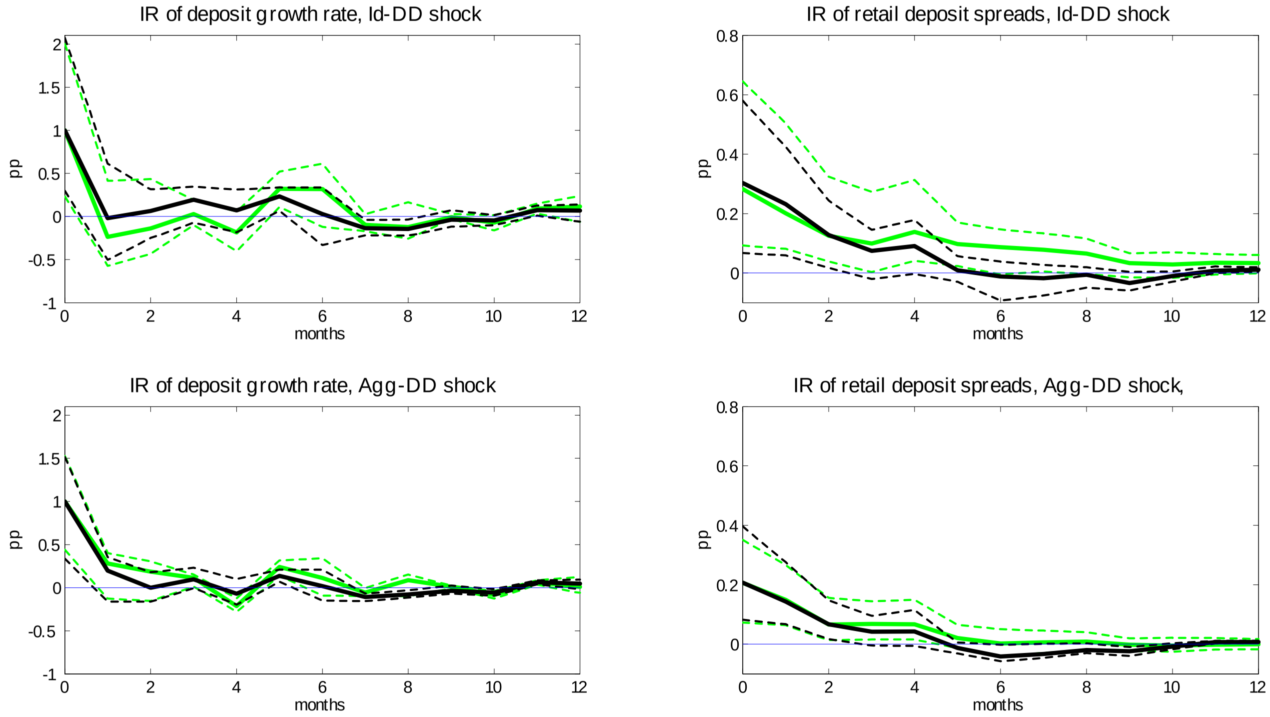

Figure 5: Impulse responses of deposit growth rates (left panel) and retail deposit spreads (right panel) of an anonymous bank 4 in the estimation. The responses are conditional on idiosyncratic deposit demand shocks (top panel) and aggregate deposit demand shocks (bottom panel). Black lines represent the results from 'post-crisis sample' data, whereas green lines represents the results from 'full sample' data. Solid lines correpond to the median impulse responses, and dotted lines to the 16th and 84th percentile of the responses.

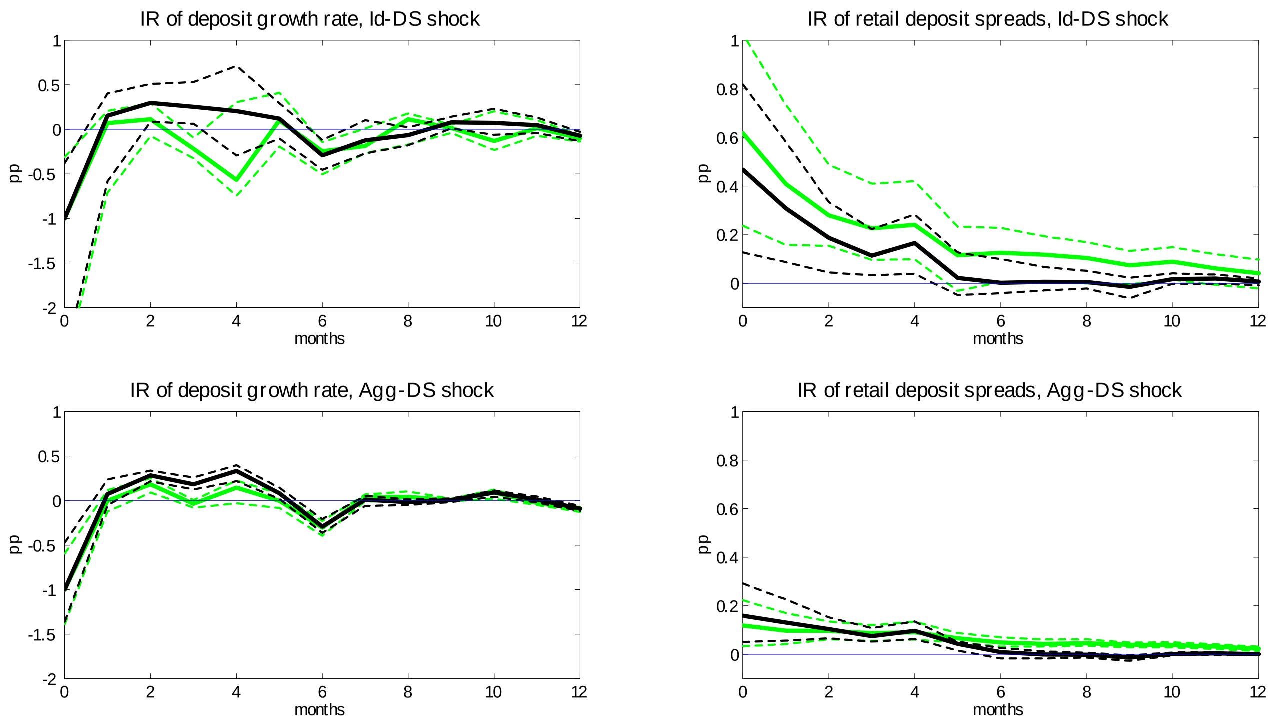

Figure 6: Impulse responses of deposit growth rates (left panel) and retail deposit spreads (right panel) of an anonymous bank 4 in the estimation. The responses are conditional on idiosyncratic deposit supply shocks (top panel) and aggregate supply demand shocks (bottom panel). Black lines represent the results from 'post-crisis sample' data, whereas green lines represents the results from 'full sample' data. Solid lines correpond to the median impulse responses, and dotted lines to the 16th and 84th percentile of the responses.

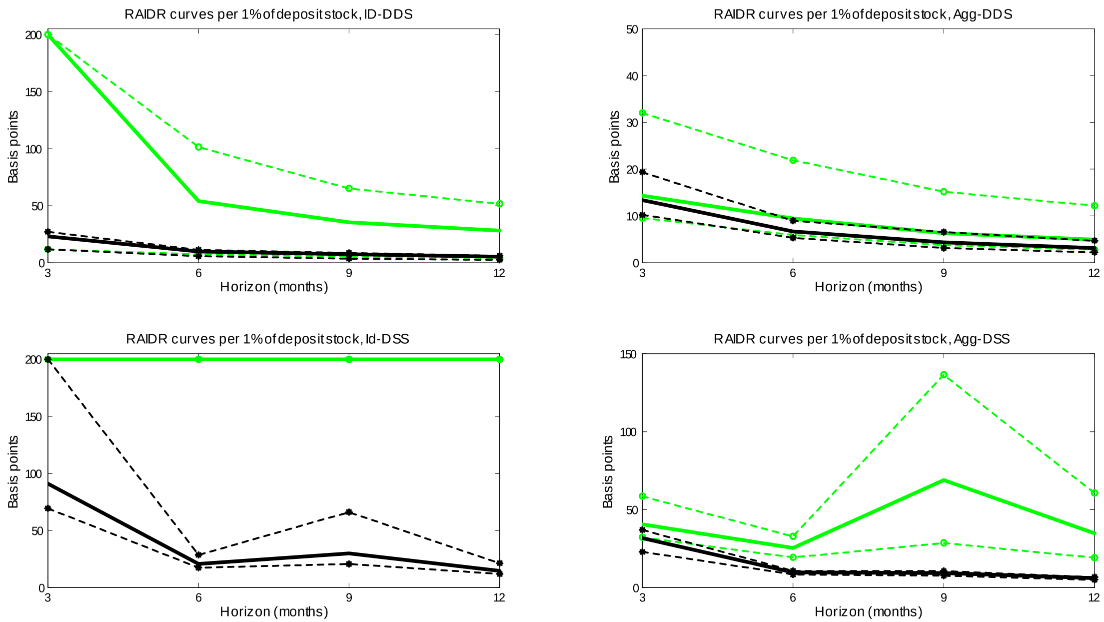

Figure 7: RAIDR curves per one percent of deposit stock size, conditional on the four identified structural shocks. Green lines denote the 'full-sample' results, whereas black lines denote the 'post-crisis' results. Computed by first transforming the impulse reponses to RAIDRs for each bank in the sample. Bold lines show the average RAIDR weighted by each bank's market share of household retail deposits, whereas dotted lines show the highest and lowest RAIDR values.