Looking beyond banks' average interest rate risk: Determinants of high exposures

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JEL classification:
G21
E43
G14

Keywords:
Interest rate risk
Banks
Tail exposures
Financial crisis

ABSTRACT

This paper studies the magnitude and determinants of interest rate risk (IRR) of listed U.S. bank holding companies. As our first contribution, we test whether banks avoid exposures to IRR as prescribed in classic bank hedging literature. To do so, we use a state space model and Kalman filter techniques to estimate time-series of interest rate betas from bank stock returns. While the interest rate exposures of banks average close to zero, we find that individual banks at times exhibit high and significant exposures to interest rate risk. As our second contribution, we relate these high betas to lagged bank characteristics from accounting data, applying logit regressions and unconditional quantile regressions. We find that high exposures are partly systemic and comove with bank characteristics like size or leverage. This has implications for the monitoring of interest rate risk by regulators and investors as well as for the ongoing debates on the appropriate capitalization of banks.

1. Introduction

We study the exposures to interest rate risk (IRR) of U.S. bank holding companies, since IRR is a systematic risk basic to all banking activities. Classic bank hedging literature suggests that elimination of easily hedgeable systematic risks is the optimal risk policy.[1] We examine whether banks follow this advice by maintaining low IRR exposures or, on the contrary, show economically significant IRR exposures at times. We further analyze if such high IRR exposures are related to unobserved system-wide factors and/or individual lagged bank characteristics. Insights gained from our analyses can aid regulators when surveilling banks' IRR and investors when judging banks' riskiness.

We contribute empirically to the existing research by adding the time-series dimension of IRR exposures to the analyses. Our empirical approach is based on Flannery and James (1984), who estimate each bank's interest rate beta from first-stage OLS regressions of bank stock returns and explain the resulting cross-section of IRR exposures with bank characteristics in a second-stage OLS regression. We extend this analysis in the time dimension by estimating banks' time-varying IRR betas in an econometrically consistent way using Kalman filter techniques. This allows us to circumvent econometric issues that emerge when using constant parameter or rolling window OLS in a context where changing sensitivities are to be expected.

Besides the theoretical implications for banks' optimal level of interest rate risk, the existing literature has not yet voiced expectations regarding the family or general shape of the distribution of IRR betas over banks and over time. Thus, we find the distribution of banks' IRR betas resulting from our Kalman filter approach interesting with regard to some features that are related to our research questions: the distribution is highly leptokurtic and centered around both a mean and a median close to zero. This implies that banks on average show low IRR exposures in accordance with the above-mentioned hedging theory. However, looking at the tails of the exposure distribution, we find that there are economically significant (i.e. high[2]) IRR betas for individual banks at some points in time.

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[1] See, e.g. Diamond and Dybvig (1983) and Froot and Stein (1998).

[2] We term both highly negative and highly positive IRR betas as high here and in the rest of the paper, as they pose high IRR exposures in absolute terms. If there is a need to differentiate between the direction of the exposure, this will be indicated.

In fact, modern banking theory acknowledges and leaves room for banks retaining high exposures to IRR:[3] according to Allen and Santomero (1997), financial intermediation has increased in spite of a reduction in transaction costs and asymmetric information. Nevertheless, financial intermediation activities shift towards managing and sharing risks and facilitating participation in ever more complex capital markets. These services entail risk management and trading by financial intermediaries themselves. Going a step further, there are papers on the allocation of aggregate risk in the economy (e.g. Hanson, Shleifer, Stein, & Vishny, 2014; Hellwig, 1994, 1998) that recognize and rationalize risk-taking. Empirical research, too, has never doubted that banks take high net positions in IRR. As one of the latest works in this field, Begenau, Piazzesi, and Schneider (2013) explicitly estimate the net interest rate exposure of banks' portfolios using on- and off-balance sheet data.

We next analyze whether high IRR betas in the tails of the exposure distribution are related to lagged bank characteristics and/or systemic effects or whether they are mere spurious phenomena resulting from estimation error and posing no threat to banks or the banking system. As a first step, we check the switching behavior of banks in and out of the high exposure tails. Banks' business models and tactical and strategic decisions in terms of risk management usually do not change too rapidly over time. Thus, IRR betas possibly related to them should not fluctuate too strongly in and out of high exposure quantiles either. We find that there is quite a high degree of stability with respect to banks' positions in the exposure distribution. In fact, more than 64% of observations in high beta quantiles are followed by an observation in a high beta quantile of the same sign (controlling for the panel structure of our data).

As a next step in analyzing the relationships of IRR betas with bank characteristics, we apply two different approaches: logit-style regressions and unconditional quantile regressions developed by Firpo, Fortin, and Lemieux (2009). The former can give an indication of what bank characteristics influence the probability of a bank-quarter being in the high beta quantiles of the exposure distribution. The latter allow for a differentiated analysis of links of the entire distribution of high IRR betas with bank characteristics, because relationships between the dependent variable and covariates are estimated at every unconditional quantile of the dependent variable.

We find only few weak relationships for the center of the IRR beta distribution, where low IRR exposures prevail. This makes sense economically, because these low exposures are the result of banks following the above-mentioned classic bank hedging theory. Banks following implications of this theory shield themselves from IRR by hedging activities, thereby decoupling IRR exposures from their sources.

In contrast, high IRR betas in the tails of the exposure distribution show economically meaningful and statistically significant relationships with lagged bank characteristics and time-fixed effects for both approaches, logit and quantile regressions. This indicates that high IRR betas are not purely random or spurious effects that can be ignored. They rather represent a consequence of the development of individual banks' characteristics, e.g. the degree of leverage or the intensity of derivative usage, that are also to some degree associated with business models or risk management policies. High IRR betas are also significantly related to time-fixed effects representing unobserved systemic shifts that broadly affect the cross-section of banks.

Summarizing the individual results, leverage shows a symmetric effect on both high beta tails of the exposure distribution: it is related to an increase in the probability of exhibiting both highly negative or highly positive IRR betas in quantile regressions. Similarly, for quantile regressions, leverage is linked to increases of both negative and positive tail quantiles of IRR betas as well. This symmetric boost for high IRR exposures from leverage is visible for the financial crisis period, too. This finding corroborates the need for adequate and comprehensive capitalization of banks also with regard to term transformation and IRR on the banking book and thus adds to current discussions on further developments of capital regulation.

Greater bank size shows an asymmetric effect on the tails of the exposure distribution: it is associated with a higher (lower) probability of exhibiting highly negative (positive) IRR betas in logit regressions. Although less pronounced for times of crisis, unconditional quantile regression results mirror this asymmetric effect and show a shift to more negative IRR betas for greater size as well. This indicates that greater size, although traditionally associated with positive effects on risk, like greater potential for scale economies in risk management and regional and product diversification, is related to a shift towards more negative IRR exposures that are characteristic for traditional (i.e. positive) term transformation. These findings should be taken into consideration in the ongoing discussions on financial stability.

Another interesting link concerns the intensity of interest rate derivative usage. Over the entire sample period, but not for the crisis subperiod, it is related positively to the positive beta tail (both in terms of probability and tail values). As this is the part of the IRR beta distribution where banks have decoupled themselves from the traditional term transformation, this link serves as an indication of banks' intention when using IRR derivatives.

Other variables show more mixed results for the different approaches and (sub)sample periods. For example, the positive link of a greater traditional term transformation with the negative tail of the exposure distribution (both in terms of probability and tail values) is significant throughout only for the crisis subperiod. Nevertheless, this result for maturity mismatch is in line with the latest theoretical literature on financial intermediation (e.g. Brunnermeier & Oehmke, 2013; Farhi & Tirole, 2012), which sees an aggregate maturity mismatch at the heart of the recent banking crisis.

Overall, our approach sheds further light on the extent and determinants of IRR exposures of banks. We show that at some points in time some banks have economically significant IRR exposures that are related to system-wide unobserved effects and bank characteristics like leverage, size, intensity of derivative usage or term transformation. This indicates that banks' significant IRR exposures can be identified to some degree by such leading indicators of high exposures, thereby helping regulators and investors to evaluate the IRR exposures of banks. Our findings also add to ongoing discussions on adequate bank capitalization and size.

The rest of the paper is organized as follows: Sections 2 and 3 give a short overview of the related literature and describe the data. Estimation of IRR betas is covered in Section 4. Section 5 contains the second-stage analyses explaining high IRR betas with lagged bank characteristics, which in turn are described in Section 5.1. Section 5.2 describes the regression design for the second stage. Sections 5.3 and 5.4 show results for logit and unconditional quantile regressions, including robustness (Section 5.4.2) and financial crisis subperiod analyses (Section 5.4.3). Section 6 concludes with possible applications of our findings.

2. Related literature

As mentioned above, our analysis rests on the basis of the fundamental paper by Flannery and James (1984), who investigated

[3] An earlier stage model by Deshmukh, Greenbaum, and Kanatas (1983), too, rationalizes risk-neutral banks taking on interest rate risk as a reaction to levels of loan and borrowing rates and associated volatilities.

how changes in the value of banks' equity are linked to interest rates. In a first stage, they therefore estimated one interest rate beta for each bank's time series of stock returns in a two-factor model specification based on Stone (1974). They found banks' stock returns to be negatively related to increases in the level of interest rates. In a second-stage OLS regression, they related the resulting cross-section of OLS-based IRR betas from the first-stage to bank characteristics. They found that the relation of bank stock returns with interest rates expressed by IRR betas is stronger for banks with higher maturity gaps. The authors interpret this finding as banks being exposed to IRR from term transformation.

This approach has since been the basis for many studies of interest rate risk that found the same results, e.g. Saunders and Yourougou (1990) or Kwan (1991),[4] but also for studies broadening the scope of the analyses to include many more variables related to banks' risk management practices and business models. Additional variables have partly been employed as control variables, but some studies sought to dig deeper into sources of IRR and thus focused on the relationships of newly added variables with IRR exposures.

One area that has captured special attention is related to derivative usage. Two important papers in this area are Choi and Elyasiani (1997) and Hirtle (1997). Choi and Elyasiani (1997) use foreign exchange risk as an additional factor and show that IRR betas of bank holding companies are generally negative but positively related to interest rate derivative usage. A similar result is found by Hirtle (1997) who measures IRR betas for each bank at yearly intervals to arrive at a panel structure for the second-stage analyses. They show that on-balance sheet portfolio composition is an important determinant of interest rate risk but that derivative contracts played an important role for the later subsection of the study (early 1990s). For that period a higher degree of interest derivative contract usage is related to higher IRR.

Schrand and Unal (1998) analyze the relation between credit and interest rate risk for banks' risk management. Their version of risk management, coordinated risk management, views credit risk with associated selection and monitoring tasks as a core-business risk, as related high-information activities allow banks to earn rents for superior evaluation capabilities with regard to the contained unsystematic risk. In contrast, homogenous risks like IRR based on efficient (observable) market prices hardly allow banks to earn rents when taking these risks. Coordinated risk management thus entails hedging homogenous risks like IRR and increasing core business risks like credit risk, when total risk is limited by regulatory restrictions. In a somewhat related study Bessler and Kurmann (2014) show that both credit risk and IRR are risk factors priced in banks' stock returns, although with changing degrees of importance and changing signs.

3. Data

Our sample consists of traded U.S. bank holding companies (BHCs)[5] that file quarterly FR Y-9C reports with the Board of Governors of the Federal Reserve System (FED). Return data of these banks and a value-weighted U.S. total market index are obtained from Thomson Reuters Datastream.[6] Information on government bond interest rates from Gurkaynak, Sack, and Wright (2006) are made available via the FED. This data and returns are used below to estimate time-varying IRR betas individually for each BHC.

Resulting IRR betas are then related to bank characteristics consisting of on- and off-balance sheet data from quarterly regulatory reports. Consolidated financial data at the BHC level are made available in FR Y-9C reports; additionally, we aggregate subsidiary data contained in the Call Reports, available via the Chicago FED and the FDIC, by summing across commercial banks of each BHC to gain additional information on, e.g. type and maturity of deposits.[7]

We restrict our analysis to domestic BHCs with charter type BHC. To ensure consistent time-series, we drop lower-tier BHCs (defined as being owned by another BHC by more than 50% of equity) and BHCs with total consolidated assets of less than \$500 million (in 2006:Q1 dollar terms).[8] To avoid including IRR measures biased by near default, we drop bank-quarters marked as liquidation, inactivity or failure (with and without resolution arranged by a regulatory agency) and bank-quarters exhibiting negative values of equity or leverage ratios of above 66 (25 observations).[9] To filter remaining BHCs for business models nonrepresentative of the concept of commercial banking, we exclude bank-quarters with loan-to-deposit ratios greater than five (10 observations) and with non-interest income amounting to five times interest income (99 observations). Following Whited and Wu (2006) we require individual banks' time-series of matched FR Y-9C, Call Report and IRR beta data to be at least eight quarters in length.

The sample period lasts from 1995:Q2 to 2012:Q4, with the main restricting factor being the availability of data on fair values of interest rate derivative contracts. This results in an unbalanced panel of 354 unique BHCs and 12,610 bank-quarters. The average time span covered for a BHC is 35.6 quarters and one quarter contains 177.6 BHCs on average. This is in line with recent studies that also combine regulatory data on the BHC (and commercial bank) level with market data on these banks (Brunnermeier, Dong, & Palia, 2012; English, Van den Heuvel, & Zakrajsek, 2012; Zagonov, 2011).

Overall, our BHC sample strongly resembles characteristics of the entire commercial banking system. On average, our sample contains more than 80% of commercial banks' aggregate total assets as reported in the FED's H.8 release. Time-series descriptive statistics of total assets-weighted balance sheet ratios of our sample are quite similar to the ones that can be calculated from the H.8 release. Deviations (less than 10*pp*), e.g. for the reliance on deposit finance or the share of total loans to total assets resemble the greater size of BHCs compared to smaller commercial banks not included in our sample. Correlations over time between respective ratios exceed 80%, with the only exception being the loans-to-assets ratio, with a correlation of 65%.

4. Estimation of time-varying IRR exposures

4.1. Research design

As our first research question, we ask if banks show IRR exposures according to classic bank hedging literature. To draw inferences on banks' IRR exposures, we estimate IRR betas from bank stock returns based on the Flannery and James (1984) unconditional two-factor model. In order to extend this model in the time

[4] For a comprehensive survey of the literature, see Staikouras (2006).

[5] We use the expressions "BHC" and "bank" interchangeably. When referring to banking subsidiaries of BHCs, we use the term "commercial bank".

[6] We follow Ince and Porter (2006) in screening the return data.

[7] We follow, e.g. Kashyap, Rajan, and Stein (2002) and Begenau et al. (2013), acknowledging the same biases in these variables (like the double counting of inter-subsidiary business or the omission of non-bank activities).

[8] See Micro Report Series Description, http://www.federalreserve.gov/reportforms/mdrm/pdf/BHCF.PDF "Beginning March 31, 2006, the FR Y-9C and the FR Y-9LP filing threshold was increased from \$150 million to \$500 million or more and the reporting exception that required each lower-tier bank holding company with total consolidated assets of \$1 billion or more to file the FR Y-9C was eliminated.".

[9] This equals dropping bank-quarters with equity capital ratios of below 1.5% and includes bank-quarters with a risk-adjusted Tier 1 capital ratio below 5%.

dimension to obtain time-varying IRR betas, we set up the following state space model for each bank i

$$r_{i,s} = \beta_{i,M,s} r_{M,s} + \beta_{i,IR,s} r_{IR,s} + \sigma_{r_i} \epsilon_{i,s} \tag{1}$$

$$\begin{bmatrix} \beta_{i,M,s+1} \\ \beta_{i,IR,s+1} \end{bmatrix} = \begin{bmatrix} \beta_{i,M,s} \\ \beta_{i,IR,s} \end{bmatrix} + \begin{bmatrix} \sigma_{i,M} & 0 \\ 0 & \sigma_{i,IR} \end{bmatrix} \eta_{i,s} \tag{2}$$

where $r_{i,s}$ is bank i's total return, $r_{M,s}$ is the total return of the Datastream value-weighted U.S. total market index and $r_{IR,s}$ is the relative change of the U.S. 10-, 5-, or 2-year government bond spot rate in week s.[10] $\epsilon_{i,s}$ represents an independently and standard normally distributed series of measurement errors. Transition equations for the unobserved states conditional on week s, $\beta_{i,M,s}$ and $\beta_{i,IR,s}$, are each set up as a random walk and are obtained via Kalman filtering with diffuse initialization of the initial states.[11] $\eta_{i,s}$ is a vector of two independent disturbances that are independently and standard normally distributed. $\epsilon_{i,s}$ and $\eta_{i,s}$ are uncorrelated at all times. The hyperparameters σ_{r_i}, $\sigma_{i,M}$ and $\sigma_{i,IR}$ scale the variances of the error terms and are estimated with functional restrictions to avoid negativity using maximum likelihood.

In the setup outlined above, we model the instability of factor loadings over time by a state space system with a random walk in the transition equation for the unobserved states, as similar applications have shown this approach to yield superior results.[12] The resulting filtered states $\beta_{i,M,s}$ and $\beta_{i,IR,s}$ derived from applying the Kalman filter represent the sensitivity of bank i's stock return in week s to the market and interest rate factor, respectively.[13]

The thus assumed instability of factor loadings over time has become a common notion in economic and econometric literature, although mostly applied to market risk.[14] Elliott and Müller (2006) argue that under the assumption of permanent changes of $\beta_{M,s}$ or $\beta_{IR,s}$, a constant parameter representing an average (which is the result of conventional time-series OLS regressions used in earlier studies of IRR) has no interpretation when the true marginal effect is time dependent. Viewing a bank as a portfolio subject to permanent change in composition on both the asset and liability side, and considering the results of studies of market timing or derivative usage by bank managers,[15] this assumption is not hard to defend.

Earlier studies relying on rolling window OLS to obtain time-varying sensitivities face the difficulty of having to assume parameter constancy and stationarity in the residuals of the return-generating model, while arbitrarily choosing an optimal window length for which this assumption is supposed to be valid. Further econometric issues can arise if overlapping windows are used in the estimation.

Accordingly, the Kalman filter approach applied here leads to more precision in the 2-factor models in Eq. (1) for our sample of BHCs. Specificially, cross-sectional averages of root mean squared errors (RMSE) of conditional 2-factor models in the shape of Eq. (1) based on beta coefficients from 50 (253) weeks rolling window OLS estimation are 5.8% (9.2%) above RMSEs resulting from the Kalman filter approach (difference in means statistically significant above the 1% level). Additionally, the Kalman filter betas' edge in fit in the conditional factor models is not simply achieved by a higher random oscillation of betas: the cross-sectional average of time series standard deviations of IRR betas from Kalman filtering is almost 40% lower than that of rolling window OLS (difference in means statistically significant above the 1% level). This strongly indicates that the Kalman filter approach applied here yields coefficients that are more stable and less contaminated by noise and thus convey greater explanatory power and information on BHCs exposures to IRR. This ensures robustness of the results presented below with regard to measurement error of IRR betas in comparison with the estimation approaches traditionally applied in the literature.

4.2. *Estimated time-varying IRR betas*

Results from the estimation described above allow us to draw conclusions on our first research question: to what extent are banks exposed to IRR and to what extent are they acting in accordance with classic bank hedging theory? Table 1, Panel A shows summary statistics of the pooled distributions of quarterly IRR betas for different maturities of the interest rate factor used in Eq. (1).[16] The distributions are centered around the slightly negative but close-to-zero means and medians. While statistically significantly different from zero, magnitudes of average IRR betas are economically insignificant: a standard deviation shock of weekly relative changes in, e.g. the 10-year spot rates indicates an annualized return for the average IRR beta of around −0.5%.

To offer more perspective on the behavior of betas within banks over time, Table 1, Panel B shows the cross-sectional distribution of standard deviations of banks' IRR beta time-series. Average volatility is 0.128, which is more than five times the average IRR exposure. There are banks in our sample that exhibit lower or even higher volatility of IRR exposures over time.

To gain deeper insight into the persistence of IRR betas we define an ordinal variable, D_{1090}, that takes on the value of 1 (−1) for bank-quarters with highly positive (negative) IRR betas, defined as being above the 90%-quantile (below the 10%-quantile), and 0 for the remaining low IRR betas in the center quantiles. Table 1, Panel C shows transition frequencies controlling for the panel structure of the data and each bank's individual observation history. We find that high exposures are quite stable: 64% of bank-quarters with high exposures (positive and negative) are followed again by a high exposure of the same sign. Of the remaining bank-quarters 7% keep a high exposure value but of opposite sign and 28% are followed by a low exposure. Low IRR-betas are even more stable: 93% of bank-quarters with low IRR betas are followed by bank quarters with low IRR betas. In the rest of the cases the IRR exposures change to a high exposure.

These relative frequencies of changes in IRR betas from high to low and vice versa show that IRR betas estimated for our sample are, in general, not switching frequently between high and low exposures but are developing quite stably. This degree of persistence can be seen as a first indication of IRR betas being related to banks' business models and (IRR) risk strategies, as they also generally tend to evolve slowly over time.[17]

It can be seen from the results, too, that the distribution is negatively skewed and highly leptokurtic. This means that compared with a normal distribution, its mass tends to lie close to

[10] I.e. negative IRR betas indicate a ceteris paribus negative bank stock return for increases in the respective interest rate.

[11] States estimated on less than two years (=104 weekly observations) of bank return data after diffuse initialization are dropped from further analyses.

[12] See, e.g. Mamaysky, Spiegel, and Zhang (2008), Mergner and Bulla (2008) and Choudhry and Wu (2008).

[13] In contrast to smoothed states which are estimated on the entire sample data, the filtered state at time s is conditional on information up to time s only.

[14] See, e.g. Jagannathan and Wang (1996) for theory and Patton and Verardo (2012) for a recent application. This direction of future IRR research for banks has already been initiated by Kane and Unal (1988) and Kane and Unal (1990).

[15] See, e.g. Faulkender (2005), Hirtle (1997) and Schrand (1997).

[16] As each quarter's last weekly IRR beta is later matched to end-of-quarter bank characteristics, we already present results and base the following arguments on each quarter's last weekly IRR betas to conserve space. As is expected from a measure without unit like a regression coefficient, distributions of IRR betas at the weekly frequency are highly similar and this approach does not change conclusions drawn in this section. Descriptive statistics of IRR betas at the weekly frequency can be obtained from the authors on request.

[17] We thank an anonymous referee for pointing this out.

Table 1
Summary statistics of estimated IRR betas.

Panel A: pooled distribution									
	Percentile					Mean	Std. dev.	Skew.	Kurt.
Maturity of interest rate factor	1%	10%	50%	90%	99%				
10 years	−0.588	−0.175	−0.022	0.140	0.505	−0.022	0.245	−3.3	543.7
5 years	−0.767	−0.154	−0.017	0.113	0.506	−0.024	0.250	−3.4	205.8
2 years	−0.631	−0.132	−0.017	0.086	0.463	−0.025	0.222	−3.6	200.5
Panel B: cross-sectional distribution of standard deviations of banks' IRR beta time-series									
	Percentile					Mean	Std. dev.	Skew.	Kurt.
Maturity of interest rate factor	1%	10%	50%	90%	99%				
10 years	0.014	0.027	0.067	0.255	1.019	0.128	0.200	5.7	49.6
5 years	0.009	0.022	0.054	0.270	1.022	0.123	0.212	4.9	37.3
2 years	0.005	0.015	0.045	0.245	1.061	0.110	0.202	4.9	37.2

Panel C: transition frequencies for ordinal variable D_{1090}			
D_{1090}	Following bank quarter		
Preceding bank quarter	−1	0	1
−1	64.1	28.3	7.5
0	3.3	93.4	3.3
1	7.0	28.5	64.5

Panel A shows summary statistics of the pooled IRR betas estimated from the state space systems characterized by Eqs. (1) and (2) for three different maturities of the interest rate factor, *IR*. The first 104 weekly values for each bank are dropped to allow for the diffuse initialization of the Kalman filter. The last value of the weekly IRR betas of each quarter is matched with accounting data from the preceding quarter. This results in a sample of 12,610 bank-quarters from 354 unique BHCs from 1995:Q2 to 2012:Q4. Panel B shows descriptive statistics of the cross-sectional distribution of standard deviations of banks' IRR beta time-series. Panel C shows transition frequencies of an ordinal variable, D_{1090}, that takes on the value of 1 (−1) for bank-quarters with highly positive (negative) IRR betas, defined as being above the 90%-quantile (below the 10%-quantile), and 0 for the low IRR betas in the center quantiles controlling for the panel structure of the data and each bank's individual observation history.

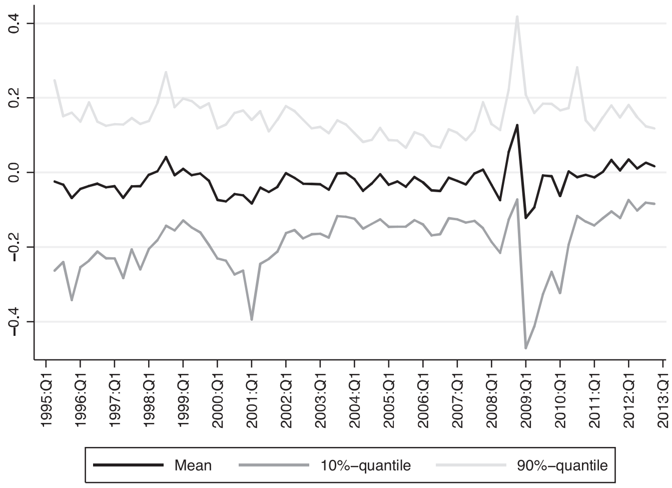

Fig. 1. Development of the cross-sectional distribution of banks' IRR beta over time. The figure shows the development of the cross-sectional distribution of banks' IRR betas on the basis of the mean, 10%- and 90%-quantiles over the sample period.

the center and in the tails. IRR betas in the tails constitute economically high exposures: a standard deviation shock of weekly relative changes in the 10-year (5-year, 2-year) spot rates indicates an annualized return, e.g. for the 10%-quantile of IRR betas of −4.3% (−5.7%, −7.0%).

Fig. 1 shows the development of the cross-sectional distribution of banks' IRR betas over time. Cross-sectional averages of IRR betas are pretty much close to zero over the entire sample period, except for the later stage of the financial crisis. Over time there are phases with a low cross-sectional dispersion of IRR betas and less extreme values in the tails of the distribution, e.g. in the middle of the 2000s. At the beginning of our sample period and especially in the aftermath of the outbreak of the financial crisis, IRR exposures in the tails are more pronounced.

Based on the results obtained so far, the answer to our first research question is the following: on average banks follow the arguments of the classic bank hedging literature with regard to systematic risks and avoid IRR exposures. Therefore, IRR seems to pose little danger for banks or the banking system as a whole. Nevertheless, we also find economically significant high IRR exposures that could matter to regulators and investors. This leads to our second research question: are high exposures purely random or are they linked to bank characteristics or systemic effects? In the latter cases they need to be taken into account when making investment decisions and they need to be surveilled by regulators.

5. Relationships of high IRR betas with bank characteristics and systemic effects

5.1. Bank characteristics as explanatory variables

To provide an understanding of the interrelationships determining high IRR exposures, our empirical investigation relates time-varying IRR betas to time-fixed effects and lagged bank characteristics consisting of on- and off-balance sheet data from quarterly regulatory reports. We use a broad set of bank characteristics to capture as many aspects of banks' business and risk profile as possible.[18]

The size of a bank, here described by the natural logarithm of the CPI-adjusted gross total assets (*SIZE*), is a natural choice since it is assumed to be linked to risk through many different channels that are a challenge to capture individually. On the one hand, risk reductions can be achieved by big banks through regional/global or product diversification as well as more efficient risk management or risk sharing via economies of scale and lower capital market participation costs. On the other hand, according to Demsetz and Strahan (1997), these reductions in traditional business risk together with the too-big-to-fail argument might incline big banks to take greater risks to increase expected return.

[18] For detailed definitions of the explanatory variables, see Appendix A.

Table 2
Summary statistics of bank characteristics.

Variable	Mean	Standard deviation	Percentile			Skewness	Kurtosis
			1%	50%	99%		
SIZE	22.139	1.507	20.148	21.72	27.462	1.419	5.212
LEV	11.791	3.442	6.334	11.316	22.061	3.836	42.692
LIQ	0.269	0.123	0.063	0.248	0.662	1.481	7.286
TL/TD	0.894	0.200	0.366	0.896	1.447	0.863	16.978
DTrD/TLi	0.140	0.085	0.019	0.120	0.395	1.124	4.566
TCI/TL	0.181	0.118	0.008	0.157	0.605	1.882	8.845
BUSCOMRAT	0.144	0.063	0.030	0.134	0.318	0.805	3.939
loanHHI	0.559	0.159	0.277	0.549	0.948	0.375	2.515
NII/II	0.256	0.244	0.016	0.192	1.319	3.796	24.114
ALMM	0.063	0.159	−0.301	0.056	0.447	0.040	5.015
IRCnom	0.331	2.355	0.000	0.006	11.107	11.458	154.814
IRCfvNET × 100	0.032	0.237	−0.231	0.000	0.861	10.724	244.405

Table reports the summary statistics of the independent variables. Appendix A lists the detailed definitions of the variables. Summary statistics besides skewness and kurtosis for *IRCfvNET* are multiplied by 100 to facilitate comparisons. The sample consists of 12,610 bank-quarters from 354 unique BHCs from 1995:Q2 to 2012:Q4.

Financial leverage, the ratio of total assets to total book equity capital (*LEV*), is usually inversely associated with asset risk. When risk is measured from the perspective of equity holders, as it is in our case, the expected sign of the relationship is reversed.

The ratio of liquid assets to total assets (*LIQ*) is usually viewed as a buffer to insure against higher risk. In the case of IRR of banks, this relationship might break down or be inverted. For example, an investment in liquid assets with short maturities or high repricing frequency instead of giving out long-term fixed-rate loans is a way to avoid negative effects of increasing interest rates.

The extent to which traditional loan business and the entire bank is financed by the deposit base is proxied by the loan-to-deposit ratio (*TL/TD*) and the ratio of total demand and transaction deposits to total liabilities (*DTrD/TLi*), respectively. Deposit financing is linked to lower IRR: both the Regulation Q ban on interest on these deposits and the stickiness and partial asymmetry in the pass-through of banks' retail rates documented, e.g. by Cottarelli and Kourelis (1994), Karagiannis, Panagopoulos, and Vlamis (2010) or Gropp, Kok, and Lichtenberger (2014), allows for lower costs and lower IRR when relying more strongly on deposits as a source of financing.

Looking closer at the loan portfolio of a bank, we use the share of commercial and industrial loans to total loans (*TCI/TL*), the share of unused business commitments to total assets plus unused business commitments (*BUSCOMRAT* based on Kashyap et al., 2002, and Gatev, Schuermann, & Strahan, 2009) and a Herfindahl–Hirschman-Index (*loanHHI*) from the loan category shares of commercial and industrial, agricultural, consumer, real estate and other loans.

The reason for focusing on commercial and industrial loans, which are generally only second in importance to banks behind real estate loans, is twofold: on the one hand, compared with other loan categories *TCI/TL* exhibits smaller correlations with the other independent variables. A higher *TCI/TL* is thus to be interpreted on its own but also as a decrease in the share of omitted loans, especially real estate loans. On the other hand, commercial and industrial loans can be seen as a proxy for credit risk as in Schrand and Unal (1998); there, lending to commercial and industrial customers is viewed as a high-information activity, as banks can gain a comparative advantage in the evaluation of the contained unsystematic risk. Following their argument of banks using hedging techniques for coordinated risk management (i.e. hedging homogenous risks like IRR and increasing core business risks like credit risk) instead of absolute risk management, we expect a reduction of IRR exposures for increased *TCI/TL*.

Unused commitments in general and unused business commitments, *BUSCOMRAT*, even more so, as they are drawn down less evenly, represent an almost plain form of IRR exposure when left unhedged.[19] In contrast, commitments can be seen as a kind of insurance of a bank against drops in its business for times of high interest rates that it sells to its customers with a fee. This fee allows the bank to hedge the associated downside risks — maybe even at a profit, depending on its bargaining power and the efficiency of its risk management. If the IRR hedge is set up properly, a bank can thus become more positively exposed to interest rate increases. Results of Kashyap et al. (2002) and Gatev et al. (2009) regarding liquidity risk of banks point in a similar direction. Kashyap et al. (2002) find a positive correlation between unused loan commitments and transaction deposits. This indicates that banks make use of the non-perfect correlation between the liquidity needs of depositors and commitment borrowers. Gatev et al. (2009) conclude that safety-oriented funding inflows from depositors during crises "allow banks to supply credit when markets cannot or would not".

The variable *loanHHI* is used to measure concentration on the asset side, which can have different effects on risk depending on the reason for concentration: if specialization or market power are the driving factors, risk can be reduced. Contrary effects can be expected if a lack of willingness (as a management decision), ability of the risk management function or feasibility (e.g. due to locational limitations) prevent a bank from diversifying more broadly into different loan segments.

The following four variables are rather directly linked to IRR: the ratio of non-interest income to interest income (*NII/II*) describes the relative reliance on different revenue sources. An inverse relationship to IRR betas is expected.

In constructing a consistent measure of the traditional maturity gap (*ALMM*), we follow Purnanandam (2007), but keep the sign information in the difference of assets less liabilities with a maturity or time to repricing of less than or equal to one year. Specifically, an estimated positive relationship indicates higher positive IRR betas for an asset-side excess and higher negative IRR betas for a liability-side excess.

The last two variables employed concern the intensity of use and net fair value position of interest rate derivatives: for the ratio of total notional value of interest rate derivatives over total assets (*IRCnom*) we sum the notional values over all contract types. No clear expectation regarding the relationship between use of derivatives and IRR can be formulated, because it depends on the underlying intention, which can be either hedging or speculation.

[19] In this context, credit risk is often assumed to take a back seat as the bank can invoke the material adverse change clause at its own discretion to deny conversion of the commitment to a loan after a re-evaluation of the borrower.

Table 3
Correlations between the independent variables.

	SIZE	*LEV*	*LIQ*	*TL/TD*	*DTrD/TLi*	*TCI/TL*	*BUSCOMRAT*	*loanHHI*	*NII/II*	*ALMM*	*IRCnom*
LEV	−0.05										
LIQ	0.12	0.13									
TL/TD	0.12	−0.07	−0.73								
DTrD/TLi	−0.20	−0.10	0.06	−0.20							
TCI/TL	0.18	−0.04	0.08	−0.07	0.06						
BUSCOMRAT	0.50	−0.05	−0.19	0.23	−0.12	0.31					
loanHHI	−0.39	0.06	−0.12	0.13	−0.20	−0.51	−0.23				
NII/II	0.46	−0.07	0.25	−0.08	−0.06	0.03	0.28	−0.12			
ALMM	0.22	−0.13	−0.35	0.37	0.10	0.27	0.44	−0.14	0.08		
IRCnom	0.44	0.05	0.21	0.00	−0.08	0.07	0.17	−0.17	0.17	0.12	
IRCfvNET	0.37	0.00	0.06	0.09	−0.05	0.08	0.18	−0.11	0.18	0.16	0.52

Table reports Pearson correlation coefficients between the independent variables.

Rather, the estimated parameter on this variable provides an indication of the realized effect of derivative usage.

Similarly, the gap or net position of positive less negative fair values of interest rate contracts held both for trading and for purposes other than trading, scaled by total assets (*IRCfvNET*), is used here to approximate current resulting net present value of derivative IRR exposures beyond mere notional values. Positive net fair values might be viewed as a proxy for counterparty risk, i.e. the risk of the counterparty not being able to meet its obligation. In terms of interest rate risk, this might entail unexpected exposures that banks consider to be hedged by interest rate derivatives.

Table 2 presents the summary statistics. Our analysis shares some variables with other recent studies combining regulatory filings with market data (Brunnermeier et al., 2012; English et al., 2012; Zagonov, 2011). In comparison with these, *LEV*, *LIQ*, *DTrD/TLi*, *TCI/TL*, *loanHHI*, *NII/II*, *IRCnom* and *IRCfvNET* are quite similar in terms of location and dispersion parameters.

Average size of a bank is \$32.2 billion, median size is \$2.7 billion (in 2006:Q1 terms). The ratio of total loans to total deposits, *TL/TD*, is quite symmetrically distributed with more than 75% of observations showing a deposit base broad enough to finance outstanding loans. Demand and transaction deposits, *DTrD/TLi*, make up 14% on average (12% in median) of total liabilities. This is an indication of the prevalence of the classic commercial banking business model of deposit-financed loans in our sample. The maturity gap-measure, *ALMM*, is distributed around a positive mean of 6.3% with a significant portion of negative values. This shows that there is a substantial number of bank-quarters for which the usually assumed excess of short-term liabilities over short-term assets prevails.

Table 3 shows the pairwise correlations of the bank characteristics. Most variables are correlated at very low levels and no pairwise correlation reaches critical values.[20]

5.2. Regression design

To analyze links of high IRR exposures, we relate time-varying IRR betas to the above-described bank characteristics lagged by one quarter[21] and time-fixed effects, η_t. Significant links of high IRR betas with time-fixed effects show that there are common unobserved factors that drive high exposures at times. This indicates the existence of systemic effects that influence IRR exposures of highly IRR-exposed banks at the same time in a similar manner. Such behavior of IRR exposures warrants surveillance by regulators. The same is true if high IRR betas are linked to lagged bank characteristics. Our aim is to not only establish such links but to look deeper into their directions and magnitudes.

As a first step, we analyze the probability that a bank-quarter's IRR exposure lies in one of the high beta quantiles of the exposure distribution. This allows us to answer the first question relevant to investors and regulators in terms of IRR exposures:[22] which bank characteristics are likely to result in high IRR exposures? We therefore set two dummies, D_{10} and D_{90}, that take on the value of 1 if the bank-quarter exhibits an IRR beta below the 10%-quantile or above the 90%-quantile of the exposure distribution, respectively, and 0 otherwise. We run logit regressions including time-fixed effects, η_t, for D_{10} and D_{90} in the general form of Eq. (3):

$$\begin{aligned} logit(P(D_{i,q,t} = 1)) = {} & \gamma_0 + \gamma_1 SIZE_{i,t-1} + \gamma_2 LEV_{i,t-1} + \gamma_3 LIQ_{i,t-1} \\ & + \gamma_4 TL/TD_{i,t-1} + \gamma_5 DTrD/TLi_{i,t-1} + \gamma_6 TCI/TL_{i,t-1} \\ & + \gamma_7 BUSCOMRAT_{i,t-1} + \gamma_8 loanHHI_{i,t-1} \\ & + \gamma_9 NII/II_{i,t-1} + \gamma_{10} ALMM_{i,t-1} \\ & + \gamma_{11} IRCnom_{i,t-1} + \gamma_{12} IRCfvNET_{i,t-1} + \eta_t \end{aligned} \tag{3}$$

To provide a deeper understanding of the links between high IRR exposures and the entire exposure distribution with bank characteristics and systemic effects, the focus of our study is on results from applying unconditional quantile regressions developed by Firpo et al. (2009) on Eq. (4).[23]

$$\begin{aligned} \beta_{i,IR,t} = {} & \gamma_0 + \gamma_1 SIZE_{i,t-1} + \gamma_2 LEV_{i,t-1} + \gamma_3 LIQ_{i,t-1} + \gamma_4 TL/TD_{i,t-1} \\ & + \gamma_5 DTrD/TLi_{i,t-1} + \gamma_6 TCI/TL_{i,t-1} + \gamma_7 BUSCOMRAT_{i,t-1} \\ & + \gamma_8 loanHHI_{i,t-1} + \gamma_9 NII/II_{i,t-1} + \gamma_{10} ALMM_{i,t-1} \\ & + \gamma_{11} IRCnom_{i,t-1} + \gamma_{12} IRCfvNET_{i,t-1} + \eta_t + \epsilon_{i,t} \end{aligned} \tag{4}$$

Unconditional quantile regressions developed by Firpo et al. (2009) show how an unconditional quantile of the pooled IRR beta distribution is affected by a small increase in an explanatory variable (controlling for the effects of other included variables). These effects are measured by coefficients for the set of independent variables in Eq. (4) that are estimated in separate unconditional quantile regressions for each unconditional quantile of the dependent variable that is of interest. Thus, coefficients can differ in sign, magnitude and significance for different unconditional quantiles of the dependent variable (IRR betas) representing heterogenous responses to independent variables (bank characteristics) at different quantiles.

[20] This is also reflected in the variance inflation factors (VIF): mean VIF of the variables is 1.76 with *SIZE* exhibiting the highest value of 2.81.

[21] As in Brunnermeier et al. (2012) we link the last value of bank i's market-perceived IRR exposure in quarter t, called $\beta_{i,IR,t}$, to the bank characteristics reported at the end of the preceding quarter, $t-1$.

[22] We thank an anonymous referee for this suggestion.

[23] We are grateful to Nicole Fortin for providing the accompanying STATA ado-file on her homepage.

Table 4
Logit regressions for the 10%- and 90%-quantile.

		Maturity of interest rate factor					
		10 years		5 years		2 years	
Variable	Dummy	D_{10}	D_{90}	D_{10}	D_{90}	D_{10}	D_{90}
SIZE		0.3487***	−0.2283**	0.4441***	−0.4283***	0.4176***	−0.4405***
		(0.1046)	(0.1032)	(0.1067)	(0.1032)	(0.1051)	(0.1076)
LEV		0.0617***	0.0838***	0.0300**	0.0473***	0.0202*	0.0176
		(0.0139)	(0.0126)	(0.0130)	(0.0116)	(0.0121)	(0.0110)
LIQ		−3.1411***	2.8720***	−2.3455**	1.8643**	−2.4743**	−0.7191
		(0.9191)	(0.9132)	(0.9761)	(0.9187)	(1.0207)	(0.9739)
TL/TD		−1.0341*	0.4698	−1.2952*	0.7082	−1.6674***	−0.5552
		(0.5379)	(0.5872)	(0.6525)	(0.5449)	(0.6025)	(0.5995)
DTrD/TLi		−1.2706	5.1562***	−1.2935	3.1729***	−0.2387	1.7093**
		(0.9001)	(0.7855)	(1.0049)	(0.7757)	(1.0395)	(0.7911)
TCI/TL		0.4949	−0.8706	0.0421	1.2898	0.4508	0.8256
		(1.0674)	(0.9947)	(1.0859)	(1.0321)	(1.1150)	(1.0534)
BUSCOMRAT		1.4433	1.5433	0.3326	0.0783	−2.7660*	2.1890
		(1.4636)	(1.4312)	(1.5519)	(1.4445)	(1.5565)	(1.4909)
loanHHI		4.2011***	−1.5152**	4.1898***	−0.7752	3.7277***	1.2591*
		(0.8007)	(0.7141)	(0.7967)	(0.7293)	(0.7857)	(0.7400)
NII/II		−0.2919	−0.2069	−0.6424*	−0.4272	−0.6195*	−0.9906**
		(0.3233)	(0.3090)	(0.3901)	(0.3810)	(0.3763)	(0.3909)
ALMM		−2.9661***	1.4775***	−1.1337**	1.5847***	0.3607	1.5395***
		(0.5207)	(0.4956)	(0.4978)	(0.4717)	(0.4968)	(0.4855)
IRCnom		0.0567	0.1047***	0.0358	0.1321***	−0.0325	0.0898**
		(0.0404)	(0.0369)	(0.0401)	(0.0394)	(0.0460)	(0.0449)
IRCfvNET		−16.1406	29.0391	30.4330	14.9125	32.6255	88.9981***
		(22.0194)	(25.1204)	(20.2711)	(26.3361)	(24.0162)	(25.9466)
Observations		12,610	12,610	12,610	12,610	12,610	12,610
Quarter FE		Yes	Yes	Yes	Yes	Yes	Yes
$p > \chi^2$		0.00	0.00	0.00	0.00	0.00	0.00

Table reports results from panel random effects logit regressions on Eq. (3) including quarter-fixed effects with dichotomous dependent variables D_{10} and D_{90}, respectively, that take on the value of 1 if the bank-quarter exhibits an IRR beta below the 10%-quantile or above the 90%-quantile, respectively, of the exposure distribution and 0 otherwise. Results are reported for the three different maturities of the interest rate factor, *IR*, in Eqs. (1) and (2). $p > \chi^2$ indicates p-values from Wald χ^2 tests for model fit. The shares of panel-level variance components to total variance are statistically significantly different from zero for all specifications above the 1%-level. Standard errors are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

The quantile regression approach thus additionally allows us to analyze how changes in bank characteristics are linked to changes in the distribution of IRR betas in a non-linear way. Hence, besides establishing links beyond mere location shifts (as already provided by OLS regressions), unconditional quantile regressions give an insight into possible scale/dispersion shifts, asymmetric effects or changes in skewness linked to changes in covariates. Furthermore, unconditional quantile regressions are more robust to departures from normality than linear estimators.[24] As the distribution of IRR betas to be analyzed here is skewed and highly leptokurtic, this econometric approach, which considers wider distributional effects, seems appropriate for our research question.

In our sample we do find highly positive and highly negative exposures in the tails of the IRR beta distribution that we focus on in our analysis for links with bank characteristics. Including only these high IRR betas in a regression would lead to a sample selection bias. But estimating the effects of bank characteristics on different quantiles of the IRR exposures distribution via unconditional quantile regressions allows us to analyze how bank characteristics (and time-fixed effects) are related to high IRR exposures that we find at the low and high quantiles. Thus, e.g. coefficients for the 10%-quantile of the IRR beta distribution tell us how the 10%-quantile is affected by changes in bank characteristics by answering the question: does an increase in a bank characteristic lead to the 10%-quantile being higher, lower or unchanged? This then shows us, too, how the highly negative exposures in that quantile are affected by the increase in the bank characteristic. Comparisons with coefficients of this bank characteristic at other quantiles allow the detection of a possible heterogenous influence.

5.3. *Logit analyses of estimated links between high IRR betas and bank characteristics*

As described in the research approach in Section 5.2, a first impression of links between IRR exposures and bank characteristics can be gained from logit regressions on dichotomous dependent variables D_{10} and D_{90}, respectively, that take on the value of 1 if the bank-quarter exhibits an IRR beta below the 10%-quantile or above the 90%-quantile of the exposure distribution, respectively, and 0 otherwise.

Table 4 reports results from panel random effects logit regressions on these dependent variables with right hand-side variables as in Eq. (3) including quarter-fixed effects. There, p-values from Wald χ^2 tests for model fit are all below the 1%-level. Results reported for the three different maturities of the interest rate factor, *IR*, in Eqs. (1) and (2) are quite similar in terms of sign, magnitude and statistical significance. Such logit regressions show which bank characteristics are linked to the probability of bank-quarters exhibiting highly positive or highly negative IRR betas controlling for the panel structure of the data.

As can be seen from Table 4, higher leverage, *LEV*, is related to a symmetrical increase in the probability of exhibiting high IRR betas irrespective of their sign. This result is consistent with expectations regarding the relationship with IRR betas measured from equity risk. Additionally, it is an indication that banks are not balancing IRR and risk from financial leverage from the perspective of equity holders, e.g. by decreasing the former when increasing the latter. To

[24] See, e.g. Schaeck and Cihak (2014).

some degree this could be attributed to the capital treatment of IRR on the banking book that is currently still applicable. Although there is growing international momentum to incorporate some more or less standardized form of capital charge for IRR that stems from the banking book into Pillar 1 or 2, regulations concerning this type of risk for the sampling period considered in this study mostly relied on banks' internal measurement systems (mostly some form of balance sheet simulation for predefined term structure shocks) or gap analyses when examining banks.[25]

This lack of an – internationally aligned – comprehensive capital charge for IRR from the banking book might incline banks to accept higher IRR exposures or at least keep the current level when increasing leverage and thereby their own default risk. In an extreme scenario such an increase in leverage might result from reductions in the value of equity due to compressed asset values and might go along with increased speculation on the development of interest rates via term transformation in an attempt to counterbalance lower profitability. Thus, our result on leverage can be linked to the ongoing discussion on the adequate capitalization and capital regulation of all sources of banks' risks.

Greater *SIZE*, in contrast, is related asymmetrically to a higher (lower) probability of bank-quarters exhibiting highly negative (positive) IRR betas. This indicates that in spite of the expected reduction in risk that bigger banks can achieve through more efficient risk management from scale economies and lower capital market participation costs and greater geographical and product/income diversification, greater *SIZE* is associated with a shift in the probability of a bank showing positive IRR betas to that of its showing negative ones. This is in accordance with Demsetz and Strahan (1997) who show a similar result. There and in our study, less overall business risk due to greater size, together with the too-big-to-fail argument, might incline bigger banks to accept greater IRR exposures to fill up their overall risk budget and increase expected return. Such effects might pose a threat to global financial stability and need to be kept in check by regulators with counterbalancing measures like additional capital charges for global systemically important banks (G-SIBs), as introduced within Basel III.

A similar asymmetrical structure is found for an excess of liabilities in the short-term portion of the balance sheet (indicated by a negative *ALMM*) and the degree of loan segment concentration, *loanHHI*. The reverse relationship holds for the share of liquid assets to total assets: the greater this ratio, the lower (higher) the probability of bank-quarters exhibiting highly negative (positive) IRR betas. These results indicate that the probability of exhibiting highly negative (positive) IRR betas is higher (lower) for bank-quarters characterized by a higher degree of loan segment concentration, excess of liabilities in the short-term portion of the balance sheet and less liquidity holding.

Especially interesting is the positive link found for the *ALMM* (traditional, i.e. positive, term transformation indicated by negative values for *ALMM*). Besides confirming the economic validity of IRR betas as a good IRR measure, this link shows that positive (negative) term transformation as indicated from a balance sheet gap measure is associated with a shift in probability to show IRR betas in the negative (positive) tail of the IRR beta distribution as measured from equity return data. This indicates that banks' equity investors are taking risk from on-balance sheet term transformation and associated IRR into account.

Other statistically significant asymmetrical relationships are found for the ratio of demand and transaction deposits to total liabilities, *DTrD/TLi*, and the extent of interest rate derivative usage, *IRCnom*. Bank-quarters with higher values for these variables are more likely to exhibit a highly positive IRR beta (with no significant link for highly negative IRR betas). This makes sense economically for *DTrD/TLi*, as the above-mentioned slow and asymmetric pass-through for deposit rates allows banks with a stronger deposit base to profit from rising market rates, as they can also smooth interest rates passed through to high-value relationship lending customers.[26] It is also interesting that the probability of being in the positive IRR beta tail, where IRR exposures are opposite from what is expected for traditional term transformation, is related positively to the intensity of IRR derivative usage. This result would be in line with the tendency to use IRR derivatives to hedge or maybe even overhedge IRR that stems from term transformation inherent in traditional deposit and lending business.

The logit analyses applied so far give a first indication of the relationships of high IRR betas with bank characteristics. There are several interesting links between bank characteristics and the probability of bank-quarters exhibiting highly negative and/or positive IRR betas. In the following section we will analyze these relationships more deeply by applying unconditional quantile regressions. There, we will also reflect on traditional research approaches based on OLS methods and relate the results to economic theory and earlier studies in this area.

5.4. *Unconditional quantile regression analyses of estimated links between high IRR betas and bank characteristics*

Unconditional quantile regressions show how the unconditional quantiles of a dependent variable – in our case banks' quarterly IRR betas from 1995:Q2 till 2012:Q4 – are related to right hand-side variables – in our case bank characteristics. To show the different relationships that emerge when applying unconditional quantile regressions to our dataset, we begin this section with a graphical overview of results for the entire distribution of IRR betas before analyzing the results in more detail in the following sections. Therefore, Fig. 2 shows the results, i.e. coefficients of the bank characteristics and their 95% confidence intervals, of applying unconditional quantile regressions to Eq. (4) for quantiles between 5% and 95% of the 10-year IRR beta.[27]

In Fig. 2, many variables show statistically significant links to IRR-betas at the low (high) quantiles, where highly negative (positive) IRR betas are located, but most variables show no significant link at or around the median of IRR exposures, indicating that there is no location shift in the exposure distribution associated with these variables. These results are in accordance with results from applying conventional panel OLS estimators to Eq. (4).[28]

As discussed in Section 4.2, on average banks seem to follow the suggestions of classic bank hedging literature and avoid IRR exposures. These bank-quarters at the center of the exposure

[25] See, e.g. Federal Reserve Board of Governors (1996, 2010, 2015), Section 5010.37.

[26] See, e.g. Black, Hancock, and Passmore (2007) for a recent study on this issue.

[27] Standard errors are bootstrapped from 11,000 replications. Respective figures for the 5-year and 2-year IRR betas are quite similar in terms of shape but show tighter confidence intervals.

[28] Results are not reported here in detail to keep the paper's focus on the tails of the exposure distribution, but can be obtained from the authors upon request. For the cross-section, the panel between estimator applied to Eq. (4) only shows significant links of mean IRR exposures with variables *SIZE*, *loanHHI* and *IRCnom*. The former is associated with a shift of the cross-sectional mean to the left, the latter are associated with a shift to the right. Other variables are not related. The fixed-effects panel estimator applied to Eq. (4) shows significant links over time only for three variables: higher loan segment concentration and a greater excess of short-term liabilities over short-term assets (i.e. a negative *ALMM* indicating traditional term transformation) are associated with a mean location shift of IRR betas to the left. A higher ratio of demand and transaction deposits to total liabilities shifts means to the right. Other variables are not related. Considering that we find the IRR beta distribution's mean and median located close to zero, these results are not surprising.

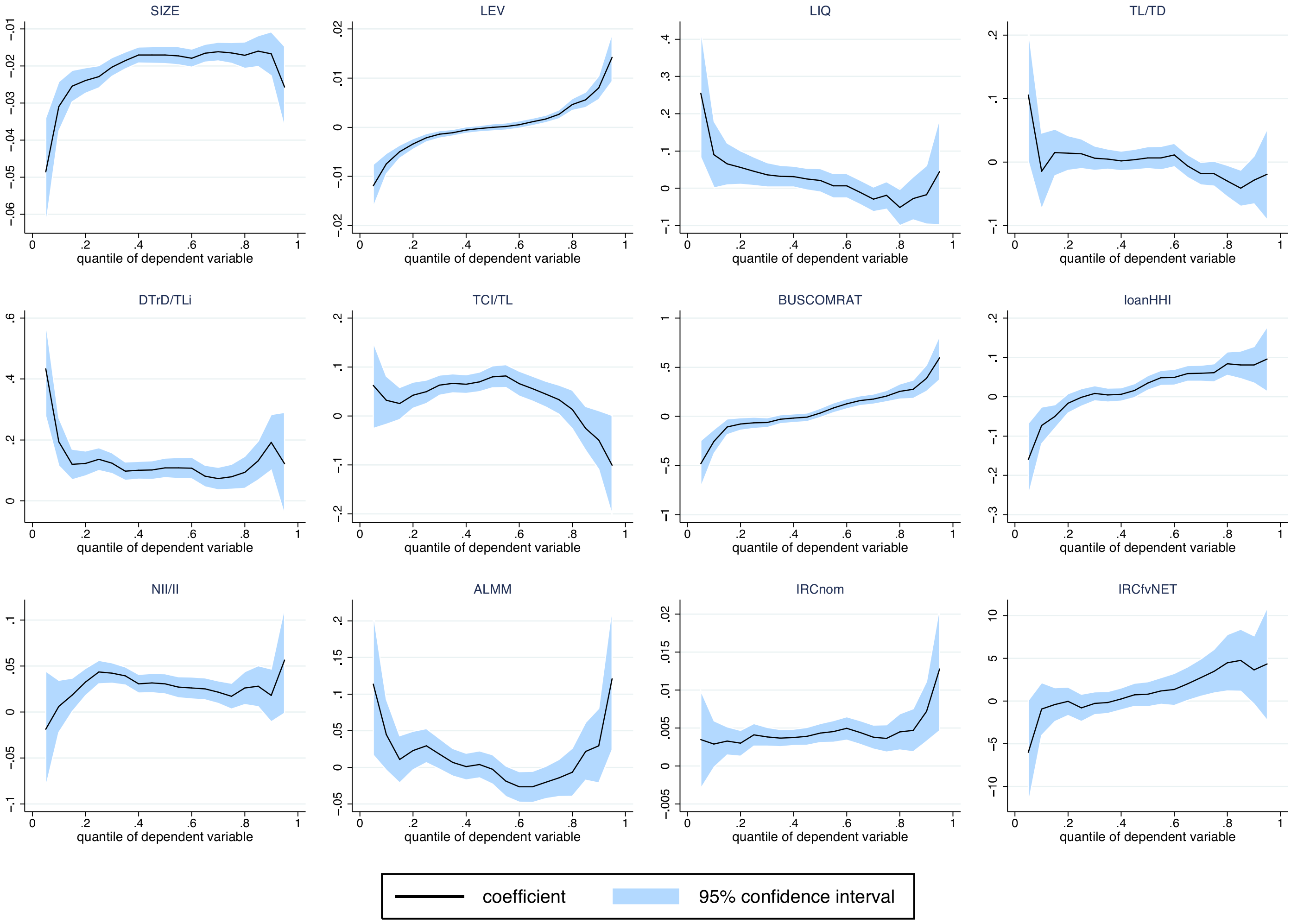

Fig. 2. Coefficients over quantiles for the full sample. The figure shows coefficients (solid line) and 95% confidence intervals (shaded area, calculated from standard errors bootstrapped with 11,000 replications) of the independent variables for unconditional quantiles from the 5%- to the 95%-quantiles of the 10-year IRR beta (horizontal axis).

distribution seem to be at least partially hedged against IRR that arises almost naturally from banks' risk transformations. For these bank-quarters at the center of the exposure distribution, we find only few significant and economically meaningful links with bank descriptive variables. This makes sense as a hedged position exhibits at most weakened links between the source of risk and its realization. Again, this is why we focus below on the tails of the IRR exposure distribution, where we find economically significant IRR betas. Unconditional quantile regressions allow us to analyze links of bank characteristics at different degrees of exposure and thus get a better understanding of their differentiated relationships with changes in location, scale, skewness and the shape of the IRR exposure distribution in general.

5.4.1. *Unconditional quantile regression results*

Table 5 shows the detailed results of unconditional quantile regressions for Eq. (4) at the 10%- and 90%-quantiles for the set of independent variables, including quarter fixed effects. This choice of quantiles is the result of a trade-off between accounting for the leptokurtic distribution of the IRR betas and analyzing quantiles that include a sufficient number of data points for the results to be interpretable and still be representative of a large enough share of the data to be economically meaningful. Standard errors are bootstrapped from 11,000 replications. Overall, results for the different maturities of the interest rate factor used for the estimation of the IRR betas are quite similar in terms of sign, magnitude and statistical significance.

As with logit regressions in Section 5.3, we find symmetrical and asymmetrical links indicating increases or decreases in risk. The most prominent result for a symmetrical link is again leverage. *LEV* shows a significant negative loading for the 10%-quantile and a significant positive loading for the 90%-quantile with a significant difference between both loadings (also see Fig. 2 for graphical proof). This indicates that for both tails of the IRR exposure distribution, increases in leverage are associated with higher IRR exposures. This result adds to the findings from logit regressions above in that not only the probability of exhibiting a high IRR beta is related to a high leverage but also the magnitude of IRR betas, i.e. given a high IRR beta an increase in leverage leads to even higher betas.

Further symmetrical effects increasing IRR in both tails – although not consistent with logit regression results – are found for *BUSCOMRAT* and *loanHHI*. As expected from Section 5.1, unused business commitments can alter IRR exposures in both directions depending on the degree of bargaining power and hedging efficiency. The results for *loanHHI* indicate that banks accepting a higher concentration of their loan business segments are similarly tolerating higher IRR exposures. Unfortunately, the reasons for this kind of parallel risk management strategy cannot be analyzed further from our data. Nevertheless, both results warrant stronger surveillance by regulators in terms of risk policies and processes for banks that show higher levels of unused commitments and loan segment concentration.

We find the opposite symmetrical effect, i.e. decreasing IRR betas in both tails, for the degree of liquidity holding. Results

Table 5
Unconditional quantile regressions for the 10%- and 90%-quantile.

Variable	Quantile	Maturity of interest rate factor					
		10 years		5 years		2 years	
		10%	90%	10%	90%	10%	90%
SIZE		*−0.0310****	*−0.0167****	*−0.0391****	*−0.0111****	*−0.0295****	*−0.0077****
		(0.0034)	(0.0030)	(0.0037)	(0.0027)	(0.0032)	(0.0022)
LEV		*−0.0074****	*0.0080****	*−0.0076****	*0.0075****	*−0.0062****	*0.0061****
		(0.0011)	(0.0012)	(0.0012)	(0.0011)	(0.0010)	(0.0009)
LIQ		0.0903**	−0.0174	*0.117***	*−0.0760***	*0.227****	*−0.111****
		(0.0455)	(0.0398)	(0.0491)	(0.0364)	(0.0393)	(0.0310)
TL/TD		−0.0143	−0.0282	*−0.0452*	*0.0320*	0.0322	−0.0038
		(0.0307)	(0.0194)	(0.0307)	(0.0200)	(0.0203)	(0.0153)
DTrD/TLi		0.194***	0.192***	0.197***	0.113***	*0.177****	*0.0252*
		(0.0408)	(0.0467)	(0.0412)	(0.0385)	(0.0331)	(0.0312)
TCI/TL		*0.0322*	*−0.0489*	0.0217	0.0189	0.0532**	0.0688**
		(0.0246)	(0.0302)	(0.0284)	(0.0329)	(0.0231)	(0.0320)
BUSCOMRAT		*−0.253****	*0.388****	*−0.245****	*0.304****	*−0.0317*	*0.210****
		(0.0624)	(0.0682)	(0.0714)	(0.0631)	(0.0538)	(0.0519)
loanHHI		*−0.0732****	*0.0810****	*−0.0805****	*0.0929****	*−0.0533***	*0.133****
		(0.0237)	(0.0237)	(0.0242)	(0.0237)	(0.0207)	(0.0230)
NII/II		0.0062	0.0179	*0.0498****	*−0.0354****	*0.0151*	*−0.0432****
		(0.0145)	(0.0146)	(0.0141)	(0.0108)	(0.0121)	(0.0085)
ALMM		0.0447*	0.0296	0.0800***	0.0298	0.0311	0.0126
		(0.0247)	(0.0260)	(0.0271)	(0.0252)	(0.0218)	(0.0215)
IRCnom		0.0029*	0.0072***	0.0034*	0.0059***	0.0017	0.0031***
		(0.0016)	(0.0020)	(0.0019)	(0.0017)	(0.0013)	(0.0011)
IRCfvNET		*−0.921*	*3.658**	*−3.922**	*2.404*	*−0.0604*	*3.143***
		(1.593)	(2.046)	(2.069)	(1.780)	(1.355)	(1.554)
Constant		0.480***	0.358***	0.670***	0.166**	0.386***	0.122*
		(0.0914)	(0.0812)	(0.0969)	(0.0740)	(0.0779)	(0.0624)
Observations		12,610	12,610	12,610	12,610	12,610	12,610
Quarter FE		Yes	Yes	Yes	Yes	Yes	Yes
R^2		0.077	0.050	0.080	0.050	0.078	0.054

Table reports results from unconditional quantile regressions on Eq. (4) at the 10%- and 90%-quantiles. The dependent variables are the matched quarterly IRR betas for the three different maturities of the interest rate factor, *IR*, in Eqs. (1) and (2). Standard errors are obtained via bootstrapping with 11,000 replications and given in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Coefficients that significantly differ at or above the 5% significance level for the 10%- and 90%-quantiles for an interest rate factor maturity are italicized.

indicate that liquidity drives the magnitude of high IRR betas towards zero, thereby reducing absolute IRR exposures and their distributional dispersion. This makes sense economically, as liquid assets due to their flexibility and short-term repricing frequency carry little opportunity costs when interest rates rise. This result does not hold consistently for all different maturities of the interest rate factor and is only in accordance with logit regression results for the negative tail, where a decrease in probability for exhibiting highly negative IRR betas is found.

We find truly asymmetric effects for *SIZE*, *DTrD/TLi* and *IRCnom* that remain unnoticed unless differentiated analyses are used for different quantiles. For *SIZE*, which is also significantly negatively related to IRR exposures at the central quantiles, we again find negative relationships that differ significantly from each other for both unconditional tail quantiles analyzed here in more detail. An increase in *SIZE* amplifies already existing negative exposures, but reduces existing positive exposures. Size is therefore not related to a reduction in absolute IRR. Its effect could rather be characterized as an asymmetrical shift of the whole distribution to the left – being more pronounced for the negative beta tail.

A similar asymmetric effect, although of opposite direction, becomes evident with the significantly positive coefficient of *DTrD/TLi* for all quantiles. An increase in the ratio of demand and transaction deposits to total liabilities reduces negative IRR exposures and increases positive exposures. This leads to the distribution of IRR betas being shifted to more positive values, which is in line with the above-mentioned literature on banks' slow and asymmetric interest rate pass-through for deposit accounts and the related smoothing of interest rates passed through to relationship-lending customers. This interpretation also holds when considering the positive tail results that are reflected in logit regression results.

Examining the use of interest rate derivative contracts reveals an asymmetric picture similar to logit regression results: negative quantiles of IRR exposures are statistically unrelated, but positive quantiles increase with higher *IRCnom*, although coefficients do not differ significantly for the 10%- and 90%-quantile. Specifically, increased usage of interest rate derivative contracts shifts the distribution of IRR betas to more positive values, indicating that banks that are more active in derivative markets are able to shield themselves better against the negative impacts of rising interest rates. This is especially interesting as the right tail of the IRR beta distribution resembles IRR exposures, contrary to what is expected for traditional term transformation. This adds to the logit regression result in a way that indicates a tendency of banks avoiding IRR from traditional term transformation to use IRR derivatives to overhedge IRR.

Looking at the time-fixed effects, we find many statistically significant values that indicate systemic effects influencing banks together at points in time beyond the impact of the bank characteristics described above. We leave determining the nature and source of this influence for future research. Nevertheless, the existence of such a common behavior of high IRR exposures alone can be dangerous for the banking system as a whole and is thus a cause of concern for regulators.

5.4.2. *Robustness*

To check our results for statistical artifacts, spurious correlations or misspecifications, we apply the unconditional quantile models above to a sample ranging only from 1997:Q2 to 2012 and use the refined maturity mismatch measure defined by English et al. (2012). It is constructed from more detailed information on maturity brackets of interest-bearing assets and liabilities available at

Table 6
Unconditional quantile regressions controlling for the financial crisis.

Quantile	10%			90%		
Variable	Regular	Crisis	Delta	Regular	Crisis	Delta
SIZE	−0.0369***	−0.0145***	***	−0.0256***	−0.0018	***
	(0.0081)	(0.0049)		(0.0083)	(0.0054)	
LEV	−0.0108***	−0.0030**	***	0.0045	0.0115***	***
	(0.0024)	(0.0013)		(0.0028)	(0.0018)	
LIQ	−0.1126	0.552***	***	−0.0078	−0.0281	
	(0.1117)	(0.0664)		(0.1286)	(0.0851)	
TL/TD	−0.1050*	0.217***	***	−0.0106	−0.0239	
	(0.0628)	(0.0357)		(0.0659)	(0.0442)	
DTrD/TLi	0.1597*	0.140***		0.0220	0.578***	***
	(0.0916)	(0.0538)		(0.1490)	(0.101)	
TCI/TL	0.0258	0.0969	**	−0.0840	−0.0199	
	(0.0789)	(0.0801)		(0.1183)	(0.0854)	
BUSCOMRAT	−0.2391	−0.163*		0.2998	0.663***	**
	(0.1572)	(0.0957)		(0.2070)	(0.140)	
loanHHI	−0.0257	−0.114***	*	0.0196	0.268***	***
	(0.0640)	(0.0403)		(0.0763)	(0.0508)	
NII/II	0.0181	−0.0459**	**	0.0262	−0.0016	
	(0.0360)	(0.0214)		(0.0426)	(0.0280)	
ALMM	−0.0157	0.0995**	**	0.0126	0.0504	
	(0.0714)	(0.0457)		(0.0858)	(0.0572)	
IRCnom	0.0053	0.0006		0.0097**	0.0026	*
	(0.0041)	(0.0021)		(0.0049)	(0.0030)	
IRCfvNET	1.3975	−10.32***	***	−1.0744	12.58***	***
	(5.080)	(3.396)		(5.7497)	(3.883)	
Constant		0.782***			0.672***	
		(0.113)			(0.0924)	
Observations		12,610			12,610	
Quarter FE		Yes			Yes	
R^2		0.089			0.060	

Table reports results from unconditional quantile regressions on Eq. (4) at the 10%- and 90%-quantiles including interaction terms with a regular times dummy taking on the value of one for the regular-times subperiod from 1995:Q2 to 2007:Q2 and zero for the crisis subperiod from 2007:Q3 to 2012:Q4. The dependent variable is the matched quarterly IRR beta for the 10-year maturity of the interest rate factor, *IR*, in Eqs. (1) and (2). Columns termed "regular" and "crisis" report coefficients for the subperiods; the regular times coefficients are obtained and tested against the null of zero as the sum of the coefficients of the respective bank characteristic and the respective interaction term. Columns termed "delta" show the level of significance of the interaction terms. Standard errors are obtained via bootstrapping with 11,000 replications and given in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

the commercial bank level Call Reports beginning 1997:Q2 to calculate a weighted average maturity gap. Results remain qualitatively unchanged.

As the two bank characteristics related to interest rate derivative contracts, *IRCnom* and *IRCfvNET*, are distributed rather non-normally, we test for a distortive influence on regression results by eliminating them from the set of independent variables. This leaves the remaining results qualitatively unchanged.

Replacing *IRCnom* with a dummy that takes on the value of 1 when the nominal value of interest rate derivatives is greater than 5% of total assets leads to qualitatively unchanged results. The choice of the cut-off for the dummy is driven by a trade-off between discretizing information contained in the derivative variable, while at the same time making sure its interpretation does not change. A pure user vs. non-user dummy, in contrast, might lead to different results because of different economic relationships. Banks that use derivatives only to a marginal degree might use derivatives for different reasons, at different costs and with different success than heavy users. In this context, Stulz (2004) concludes that derivatives can create risk, especially if a firm uses derivatives episodically and is inexperienced in their use.

Although independent variables showed no sign of severe multicollinearity, results especially for *SIZE* might be influenced by the uniform scaling of ratios by total assets as denominator. To test if this is an issue with our data, we replace *SIZE* with the natural logarithm of the CPI-adjusted market and book value of equity. Results remain qualitatively unchanged.

As some of the variables employed above, like leverage or derivative usage, could have bidirectional relationships with IRR exposures, concerns for endogeneity of regressors might arise. Concerning leverage, the use of book leverage is a first measure of precaution. The argument made above, that leaving out derivative variables does not change results, is another indication that there is also no grave problem of identification in our sample caused by endogenous regressors. What contributes to this assessment is that we relate market information to quarterly-lagged accounting data. This way, any endogeneity-inducing bidirectional relationship would need to exist over this time-lag as well. As we see no economically sound argument to support such relationships, we do not consider endogeneity to be an issue in our analyses.

5.4.3. Results for high exposures controlling for the financial crisis

Next, we extend the analysis of the relationships by controlling for the recent financial crisis. As market conditions have undergone drastic changes since the middle of 2007, it is highly interesting to see if and how the relationships found above are affected by the financial crisis.

To be able to draw inferences, we include interaction terms of each independent variable with a regular-times dummy. It takes on the value of one from the beginning of our sample in 1995:Q2 to 2007:Q2 and zero for the crisis subperiod from 2007:Q3 to 2012:Q4.[29] The columns termed "crisis" and "regular" in Table 6

[29] We base this approach on the crisis timeline of the Federal Reserve Bank of St. Louis (http://timeline.stlouisfed.org/). The rationale is that, although the direct consequences of the financial crisis might have slowly begun to attenuate by the end of 2009, the countermeasures taken by the FED and the US government lasted well into 2012 and some are still in place today.

report the resulting coefficients for the 10-year maturity of the interest rate factor in Eqs. (1) and (2) for the crisis subperiod and the regular times subperiod, respectively. Significance of differences in relationships between subperiods is represented by the level of p-values of the interaction terms in the “delta” column.

As can be seen from Table 6, for most of the variables, like *LEV*, *SIZE*, *DTrD/TLi*, *BUSCOMRAT*, *loanHHI* and *IRCnom*, relationships described in Section 5.4 are visible in terms of sign for both subperiods, but show different magnitudes and – related – levels of significance. For *DTrD/TLi*, *BUSCOMRAT* and *loanHHI* relationships described above for the entire sample period are significant for the crisis subperiod indicating that their impact on IRR exposures is especially important during such a period of market uncertainty. The increased importance of deposits as a stable source of funding, of commitment lending during times when uncertainty about the future availability of credit is widespread among customers, and of product diversification during and after the financial crisis is visible in these results.

For *LEV* and *SIZE*, relationships with the negative IRR beta tail are consistently significant throughout our entire set of analyses and for both subperiods. Although the direction of the differentiated relationships described above in Section 5.4 remains the same, there are differences in levels of significance for the positive IRR beta tail for the subperiods. The symmetrical IRR-increasing effect of leverage is there for the crisis subperiod, while the asymmetrical shift in IRR betas to more negative values associated with greater size can be found for regular times. The reduction in strength of the shift of IRR betas to the left associated with greater size might be explained with the increased probability and greater credibility for the denial of a public bail-out for bigger banks after the collapse of Lehman Brothers and related regulation, e.g. banks’ “living wills”, enacted afterwards.

Two additional interesting effects involving highly negative IRR betas become apparent: results for *LIQ* show that the risk-reducing effect we find for highly negative IRR betas in the entire sample is driven by the crisis subperiod, which is in line with recent literature viewing liquidity at the heart of the financial crisis.

In a similar manner, *ALMM* shows a significantly positive relationship with the IRR exposure at the 10%-quantile since the crisis, which is significantly different from regular times. Hence, an excess of liabilities in the short-term portion of the balance sheet (indicated by a negative sign for the independent variable) is associated with amplified negative exposure to increases in interest rates. This is in line with the aforementioned latest research on an aggregate maturity mismatch being amplified by the extremely short-term funding of securitization vehicles as a major cause of the financial crisis.

The significantly different coefficients that have emerged for *IRCfvNET* since the crisis indicate an increase in high IRR betas for positive net fair values of interest rate derivative contracts. This can be seen as a consequence of the (perception of) increased counterparty risk that resulted from the financial crisis. Stulz (2010) argues that counterparty risk is present in credit default swap markets, even though much of the direct risk due to the default of the counterparty is generally accounted for by collateral agreements. The rationale is that in the case of such a default, the surviving counterparty is exposed to risks that were considered hedged and thus has to buy new protection on the market. This way, higher positive fair values of interest rate derivatives, which were meant to protect a bank, seem to have resulted in higher IRR exposures as the reliability of this protection deteriorated.

Overall, we find altered relationships between market-perceived IRR exposures and bank characteristics for the financial crisis subperiod. The significant increase in coefficients of liquidity and maturity mismatch is a sign of markets realizing the associated build-up of risk with respect to interest rates. Both effects are found at the quantile of highly negatively exposed bank-quarters, making them even more relevant to investors and regulators.

6. Conclusion

We analyze interest rate risk exposures of U.S. bank holding companies from 1995 to 2012. As our first contribution we test whether banks show IRR exposures in accordance with classic bank hedging literature. Our approach for measuring IRR exposures is based on the traditional approach by Flannery and James (1984). We extend their model in the time dimension by applying Kalman filter techniques on a state space system that relates stock returns of banks to a market factor and an interest rate factor via unobserved time-varying sensitivities. The resulting time-varying IRR betas for each bank represent an econometrically consistent measure of the time-series of exposures to IRR as perceived by the market.

Over banks and over time we find means and medians of IRR betas slightly below but close to zero. Thus, the average IRR exposure of banks is in line with the theoretical bank hedging literature. This result at first glance depicts IRR exposures of banks to be a rather negligible source of risk, warranting little attention from regulators or investors. Nevertheless, the IRR beta distribution shows high exposures that are economically significant.

Our second contribution to the existing literature on IRR is to provide a deeper understanding of these high IRR exposures with bank characteristics from regulatory accounting data. Banks’ business models or tactical and strategic decisions in terms of risk management do not change too rapidly over time. This is why we first analyze the switching behavior of banks in and out of the central exposure quantiles and high exposure tails. Results show a quite high degree of stability with respect to their position in the distribution: more than 64% of observations in high beta quantiles are followed by an observation in a high beta quantile of the same sign. Exposures in the central quantiles are even more stable.

Applying logit analyses and unconditional quantile regressions, we find differentiated relationships of highly positive and highly negative IRR exposures with lagged bank characteristics and time-fixed effects. The latter are partly significantly different from zero in both analytical approaches applied, indicating unobserved systemic effects that broadly affect the cross-section of banks.

Our results point to strong links between bank characteristics and IRR exposures that should be taken into account by regulators to promote the stability of the banking system and by investors to better assess banks’ riskiness. The first of our key findings is the symmetrical and risk-increasing relationship of leverage with probability and magnitude of IRR betas in both exposure tails. Besides being expected for a risk measure based on equity returns like IRR betas, this result can serve as an indication of banks not counterbalancing financial leverage risk and IRR. This might be related to a lack of an internationally aligned regulation for IRR from the banking book, allowing banks to take on IRR and increase their leverage at the same time. A risk-insensitive leverage ratio is not able to keep the degree of term transformation or maturity mismatch in check either. Against this background our results add to the ongoing discussion of optimal capitalization and capital charges for banks.

Similarly, the observed shift of IRR betas to more negative values linked to increases in size needs to be considered by regulators and investors. Results indicate a shift towards negative IRR betas resembling traditional term transformation. This indicates that bigger banks do not use their overall greater potential for diversification or economies of scale to reduce total risk, but might even fill up under-used risk budgets by taking on greater IRR. To avoid negative effects on financial stability, such behavior – that might be interpreted as reliance on public bail-outs – has to be kept in check, e.g.

Table A.1
Variable definitions

Variable	Description	Calculation	Sources
SIZE	Log of gross total assets, CPI-adjusted for 2006:Q1	$\ln\left((BHCK2170 + BHCK3123 + BHCK3128) * 1000 * CPI_{2006:I}/CPI_{act}\right)$	U.S. FED FR Y-9C report, Bureau of Labor Statistics
LEV	Total assets to total equity	$BHCK2170/BHCK3210$	U.S. FED FR Y-9C report
LIQ	Liquid assets to total assets	$BHCK0010 + BHCK1754 + BHCK3545 + \begin{cases} BHCK0276 + BHCK0277 & before\ \ 1997:I \\ BHCK1350 & 1997:I\text{–}2001:IV \\ BHCKB987 + BHCKB989 & after\ \ 2001:IV \end{cases}$	U.S. FED FR Y-9C report
TL/TD	Total loans to total deposits	$(BHCK2122 + BHCK2123)\,/\,(BHDM6631 + BHDM6636 + BHFN6631 + BHDN6636)$	U.S. FED FR Y-9C report
DTrD/TLi	Demand and transaction deposits to total liabilities	$rcon2215/rcon2948$	Chicago FED Call Reports
TCI/TL	Commercial and industrial loans to total loans	$(BHCK1763 + BHCK1764)\,/\,(BHCK2122 + BHCK2123)$	U.S. FED FR Y-9C report
BUSCOMRAT	Unused business commitments to total assets plus unused business commitments	$(rcfd3423 - rcfd3815)\,/\,(rcfd3423 + rcfd2170 - rcfd3815)$	Chicago FED Call Reports
loanHHI	Herfindahl-Hirschman-Index from the loan category shares	$\left(TCI/TL\right)^2 + \left(\frac{BHCK1590}{BHCK2122+BHCK2123}\right)^2 + \left(\frac{BHCB538+BHCK2011}{BHCK2122+BHCK2123}\right)^2 + \left(\frac{BHCK1410}{BHCK2122+BHCK2123}\right)^2 + (other\ loans\ share)^2$	U.S. FED FR Y-9C report
NII/II	Non-interest income to interest income	$BHCK4079/BHCK4107$	U.S. FED FR Y-9C report
ALMM	Short-term asset-liability mismatch	In accordance with Purnanandam (2007), but keeping the sign info	Chicago FED Call Reports
IRCnom	Nominal values of all interest rate contracts to total assets	$(BHCK8693 + BHCK8697 + BHCK8701 + BHCK8705 + BHCK8709 + BHCK8713 + BHCK3450)/BHCK2170$	U.S. FED FR Y-9C report
IRCfvNET	Net fair value position of all derivative contracts to total assets	$(BHCK8733 + BHCK8741 - BHCK8737 - BHCK8745)\,/BHCK2170$	U.S. FED FR Y-9C report

by the application of Basel III risk buffers for global, systemically important banks and other nationally/regionally "bigger" banks.

Rather mixed results for other bank descriptive variables for the different approaches and (sub)samples make an overall interpretation less imperative, but some are still worth noting to show the effects of the financial crisis on IRR exposures of banks and relationships with bank characteristics. Positive net fair values of interest rate derivative contracts on the books, which can be seen as a proxy for counterparty risk, are related to an increase in high IRR exposures for the crisis subperiod. This link can be interpreted as the market realizing reduced hedging efficiency via increased counterparty (wrong-way) risk of derivatives in the time after the financial crisis. Our traditional maturity gap measure is significantly linked to the magnitude of negative tail IRR exposures only during the crisis. For this subperiod, we find that traditional term transformation is associated with increased negative IRR exposures. Additionally, for this tail of IRR exposures, liquidity has a risk-reducing effect that is only valid for the crisis subperiod. These links reflect some findings on causes for the financial crisis identified in recent literature, like Farhi and Tirole (2012) and Brunnermeier and Oehmke (2013).

Overall, we show that high IRR betas are linked to unobserved systemic effects in the financial markets and to the development of banks' characteristics that can be assumed to partially reflect their business models and risk management strategies. Regulators need to focus especially on these high IRR exposures as they might pose a threat for individual banks and possibly for the entire banking system. Investors need to take high IRR exposures into account when making decisions, e.g. regarding portfolio optimization. Our logit and quantile regression results can aid regulators and investors surveilling IRR by showing relationships with publicly available regulatory accounting information. We also add to current discussions regarding optimal capitalization and capital charges for banks as well as current regulatory initiatives.

Appendix A. Variable definitions

Table A.1

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