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ORIGINAL RESEARCH

Financial statements based bank risk aggregation

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Abstract One of the major challenges involved in risk aggregation is the lack of risk data. Recently, researchers have found that mapping financial statements into risk types is a satisfactory way to resolve the problem of data shortage and inconsistency. Nevertheless, ignoring off-balance sheet (OBS) items has so far been regarded as the usual practice in risk aggregation, which may lead to deviations in conclusions. Hence, we improve the financial statements based risk aggregation framework by mapping OBS items into risk types. Based on 487 quarterly financial statements from all 16 listed Chinese commercial banks over the period 2007–2014, we empirically study whether the overall impact of OBS activities and the individual impact of each of the OBS risk types on total risk depend on bank size. Moreover, this research divides the sample into two subsets, during and after the subprime crisis, to find out how the subprime crisis affects risks of Chinese banks. Our empirical results show that although OBS credit risk is positively linked to total risk while OBS operational risk is negatively linked to total risk for both large and small banks, the overall impact of OBS activities on total risk depends on bank size. The overall OBS activities are positively related to the large bank's total risk while they are negatively related to the small bank's total risk. Besides, we also found that it is the increase of

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liquidity risk and market risk that leads to the larger total risk of Chinese banks during the subprime crisis.

Keywords Risk measurement · Risk aggregation · Financial statements · Off-balance sheet · Chinese banking · Subprime crisis

JEL Classification G01 · G21 · G32

1 Introduction

Some characteristics of off-balance sheet (OBS) activities, such as blind expansion and high risk, made the existence of OBS activities a key factor that caused destabilization during the subprime crisis (Brunnermeier 2009). Basel II, however, was widely seen as having failed to adequately capture the risks posed by OBS activities (Acharya and Richardson 2009; Blundell-Wignall and Atkinson 2010). Essentially, OBS risk should be regarded as an indispensable part of a bank's overall risk because both on- and off-balance sheet activities create bank risks (BCBS 1986). Basel Committee has already made great strides in strengthening regulatory capital framework to cover risks, whatever the source (BCBS 2010). Thus, a reliable risk aggregation model to capture both on- and off-balance sheet risks is urgently needed.

Broadly, risk aggregation refers to a quantitative risk measurement method that incorporates multiple types of risk (Li et al. 2015). One major challenge in risk aggregation is the risk data used for establishing marginal risk distributions (BCBS 2003). Many previous studies have attempted to use simulated risk data to measure credit risk, market risk and liquidity risk (Dimakos and Aas 2004; Acerbi and Scandolo 2008), which can hardly replace the real data. For the operational risk, external real data are often used to supplement insufficient internal loss data. However, some remain skeptical of the external operational risk data (BCBS 2003; Chavez-Demoulin et al. 2006). Thus, the shortage and inconsistency of risk data limit the reliability and validity of risk aggregation results.

Recent research has, instead, used publicly available industry-wide data from a set of commercial banks' financial statements to develop empirical proxies for different risk types. Although financial statements data have some drawbacks, such as lower reporting frequency (usually published quarterly), different accounting standards across the world (Bae et al. 2008) and poor accounting quality (Saito 2012), collecting risk data from financial statements is still a satisfactory way to resolve the problems of data shortage and data inconsistency.

Some have attempted to aggregate marginal risks based on-balance sheet data. Kretzschmar et al. (2010) implement a fully-integrated risk analysis based on-balance sheet asset positions. However, the exclusion of OBS derivatives from asset portfolios weakens the effectiveness of qualitative conclusions. Given the importance of OBS items, Drehmann et al. (2010) not only take account of balance sheet assets and liabilities, which have been considered by Alessandri and Drehmann (2010) for integrating credit and interest rate risk, but also pay attention to OBS items. Such a modification makes the hypothetical bank reflect a real commercial bank more accurately.

Mapping profit and loss (P&L) items from income statement into risk types is another feasible way to obtain risk data. As researchers have realized that risk is defined in terms of earnings volatility (Rajan 2006), P&L items from income statement that are created by earnings volatility can be used as proxies for risks (Kuritzkes and Schuermann 2007). Thus, Kuritzkes and Schuermann (2007) get risk P&L successfully by mapping income statement items of US banks into risk types. Given the significant accounting difference between income statements in US and China, Li et al. (2012) use data of risk P&L to measure Chinese banks' risks by establishing a mapping relationship between Chinese banks' income statements and risk types.

Above studies merely focus on one piece of financial statements, either income statement or balance sheet, while Inanoglu and Jacobs (2009) match risk types with items from both income statement and balance sheet. In particular, the liquidity risk is mapped into balance sheet items and the credit, market and operational risks are mapped into income statement items. But this correspondence creates a problem of discrepancies in attributes of proxies for different risk types. By contrast, Rosenberg and Schuermann map risk types into income statement and balance sheet to obtain risk P&L and risk exposure, respectively. By doing so, they collect data from both income statement and balance sheet simultaneously. Although Rosenberg and Schuermann (2006) realized that OBS items can be larger and the results may be somewhat arbitrary because only on-balance sheet items are considered, they still followed the usual practice of ignoring OBS items.

To summarize, previous studies have suggested a relative complete risk aggregation framework based on financial statements by mapping balance sheet and income statement items into multiple risk types. Nevertheless, ignoring OBS items is regarded as the usual practice in risk aggregation, which may lead to deviations in conclusions because both on-balance and off-balance sheet assets are exposures to risk in the context of the generation of risk P&L items.

Since the 1980s, the product assortment of commercial banks has shifted sharply from traditional on-balance sheet activities to non-traditional OBS activities because of the tendency to avoid supervision and pursue higher yield in the midst of increasingly intense competition (Boyd and Gertle 1994). With the rapid expansion of OBS activities, they have become one of the main pillars of banks. According to the *China Financial Stability Report 2015*, at the end of 2014, OBS items exceeded seventy trillion CNY, accounting for 40.87% of total on-balance sheet assets. This suggests that as the burgeoning banking business, OBS activities have reached an important stage in the Chinese banking sector (Hou et al. 2015).

However, OBS activities trigger additional risks while bringing considerable income and the role of OBS items in systemic vulnerability was highlighted during the subprime crisis. As early as 1988, the business scope under supervision had already extended from balance sheet items to OBS items (BCBS 1988). The China banking regulatory commission (CBRC) also published a policy document titled *Risk Management Guidelines of Commercial Banks' off-balance Sheet Business* to regulate OBS activities in 2011.

In this paper, therefore, we improve the financial statements based risk aggregation framework by mapping OBS items into risk types to get more accurate and rational risk distributions. In the experiment, we construct two hypothetical banks of different sizes for comparison because the expansion of OBS activities is linked to bank size (DeYoung and Rice 2004). Through a dataset that covers all 16 Chinese listed commercial banks spanning the period 2007–2014, we aggregate credit, market, liquidity and operational risks. Then by comparing total risk with and without OBS activities, we empirically prove that OBS activities indeed affect total risk and the impact depends on bank size. Thus, ignoring OBS activities will lead to deviations in risk aggregation results. Furthermore, we analyze how the subprime crisis affects Chinese commercial banks' risks by dividing the sample into during and after the subprime crisis.

The remainder of this paper is organized as follows. The next section presents the improved financial statements based risk aggregation framework in detail. Section 3 describes data collection and preprocessing procedures and discusses the major empirical results. Section 4 concludes with a summary of findings, limitations and future research directions.

2 Approach

This section describes in detail the improved financial statements based bank risk aggregation framework.

2.1 Risks in this research

Liquidity dried up during the subprime crisis, so liquidity risk is a challenge to a bank in times of stress (Cornett et al. 2011). Hence, Basel III not only requires sound credit, market and operational risks management in pillar 1 standards but also enhances liquidity risk supervision in pillar 2 requirements (BCBS 2010). In line with Basel III, we intend to aggregate credit, market, liquidity and operational risk in this paper.

For most banks, the major risk is the credit risk that is resulted from the counterparty failure (BCBS 1988; Mustika et al. 2015). The risk of loss arising from adverse price movements in a bank's principal trading positions is referred to as market risk (BCBS 1996). Liquidity risk occurs when a bank fails to fund increases in assets or meet obligations as they become due, without incurring unacceptable losses (BCBS 2008). A widely used definition of operational risk is the loss resulting from inadequate or failed internal processes, people and systems, or from external events (BCBS 2006; Li et al. 2014).

2.2 The correspondence between risk types and financial statements

To obtain risk data from financial statements, we map income statement items and on-balance and off-balance sheet assets into risk types. Compared with the existing financial statements based risk aggregation framework, in which OBS assets are ignored, we not only establish the mapping relationship between on-balance sheet assets and risk types but also map OBS assets into risk types. Essentially, OBS risk is an indispensable part of a bank's overall risk because both on- and off-balance sheet activities create bank risks (BCBS 1986). Furthermore, the fast-growing of OBS activities makes the scale of OBS items is too large to ignore (Karim et al. 2013; Hou et al. 2015). Thus, the incremental information contained in OBS accounting disclosures (Seow and Tam 2002) make the mapping relationship proposed by us more complete and reasonable.

Then, we identify OBS items that will be incorporated into our improved risk aggregation framework. The definition of OBS activities in a narrow sense consists of commitments, guarantees, derivatives and investment banking business (BCBS 1988). In China, however, OBS financial derivatives are accounted for at fair value in the balance sheet from 2007 onwards as per the new accounting standards. Therefore, the *Risk Management Guidelines of Commercial Banks' off-balance Sheet Business* issued in 2011 by CBRC divided OBS business into guarantee business and commitment business. Unfortunately, the disclosure of OBS items is limited and varies from bank to bank. Hence, we just take part of OBS items into risk aggregation, including credit commitment, capital expenditure commitment and operating lease commitment.

The more complete and reasonable mapping relationship between financial statements and risk types is shown in Fig. 1. By mapping income statement items and on-balance and off-balance sheet assets into risk types, we obtain risk P&L and risk exposure, respectively. Although these mappings are hardly perfect, we believe they still provide a reasonable approximation of risk type attribution.

As shown in Fig. 1, credit risk exposure is equal to interest-bearing assets minus loan loss provisions, and then plus OBS credit commitment. Interest-bearing assets include loans, due from the central bank, due from banks and other financial institutions, accounts receivable investment, buying back the sale of financial assets, lending to banks and other financial institutions and bonds. OBS credit commitment is classified into guarantee business and credit business. Guarantees are regarded as direct credit substitutes (BCBS 1986) and credit business (e.g. loan commitments) is the most important OBS credit instrument (Chateau 2009). Risk P&L items that related with credit risk exposure is net

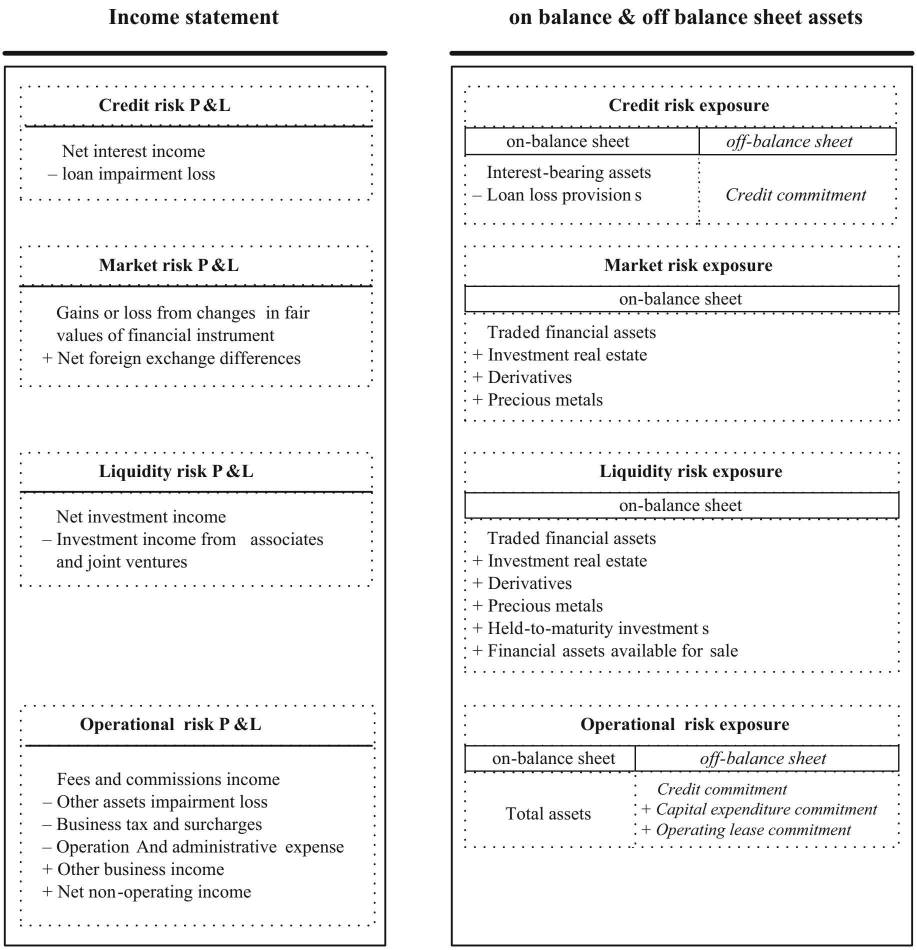

Fig. 1 The correspondence between risk types and financial statements

interest income and loan impairment loss. The reason is that changes in interest-bearing assets will lead to changes in net interest income and loan impairment loss should be recorded if there is any indication that loans have suffered an impairment loss (Kwak et al. 2009). Thus, credit risk P&L is equal to net interest income minus loan impairment loss.

With respect to market risk exposure, it includes traded financial assets, investment real estate, derivatives and precious metals because all these assets are influenced by market factors (i.e. price, interest rate, foreign exchange). Risk P&L items that related with market risk exposure is gains or losses from fair values of financial instruments and net foreign exchange differences. The reason is that gains or losses from fair values of financial instruments are affected by fluctuations in prices of financial instruments and net foreign exchange differences are determined by changes in foreign exchange. Thus, the sum of these two accounts is a proxy for market risk P&L.

Liquidity risk exposure includes traded financial assets, investment real estate, derivatives, precious metals, held-to-maturity investments and financial assets available for sale. Net investment income reflects the gains or losses from trading ready to liquidate financial assets. Investment income from associates and joint ventures is generated by long-term equity investments, which is made to control or influence other companies, not to get short-term investment income. Thus, liquidity risk P&L is equal to net investment income minus investment income from associates and joint ventures.

For operational risk, Rosenberg and Schuermann (2006) deem that all assets and activities of the bank are in some way subject to operational risk. We follow this standpoint that operational risk exposure consists of total on-balance and off-balance sheet assets. The remaining P&L items in the income statement serve as a proxy for operational risk P&L because the operational risk is the typical non-financial risk and represents volatility of residual earnings which cannot be categorized into market, credit or liquidity risk.

2.3 Procedure of risk measurement and aggregation

Risk P&L items from income statement are not comparable among different banks because banks are different in terms of scale, capital allocation, investment strategy and management level (Rosenberg and Schuermann 2006). To allow direct comparison across banks, risk P&L need to be converted into a “risk return” based measure. In accordance with Kretzschmar et al. (2010), we use the data preprocessing method to obtain a specific bank’s risk return. The procedure of data preprocessing can be divided into the following three steps:.

Firstly, we convert risk P&L into a “risk return” based measure. Since risk P&L is generated by assets that exposed to risk, an obvious approach for doing this would be to divide risk P&L by assets to yield a return on assets measure. In this paper, bank assets are defined as risk exposures. Thus, the risk return is the ratio of risk P&L to risk exposure. We then define the marginal risk return for the ith bank, jth risk in period t as

$$r_{i,j,t} = \left(\frac{R_{i,j,t}}{RE_{i,j,t}}\right) \tag{1}$$

where $r_{i,j,t}$, $R_{i,j,t}$ and $RE_{i,j,t}$ stand for the risk return, risk P&L and risk exposure of bank i, risk j in period t, respectively.

In the second step, we compute the expected risk return and deviation from risk return. The risk return can be divided into two parts: the expected risk return and deviation from risk return. The expected risk return for a bank is the average risk return over the sample period, which reflects the bank's own characteristics in terms of scale, capital allocation, investment strategy and management level. The deviation from risk return is computed by subtracting the average risk return over the sample period (expected risk return) for each bank, which reflects the macroeconomic background and operating conditions of the whole banking industry. Thus, a bank's risk return is determined by both market and individual information. Specifically, the expected risk return is defined as

$$\bar{r}_{i,j} = \left(\frac{1}{T_i} \sum_{t=1}^{Ti} r_{i,j,t} \right) \tag{2}$$

and deviation from risk return as

$$\Delta_{i,j,t} = r_{i,j,t} - \bar{r}_{i,j} \tag{3}$$

where bank i is observed for T_i periods. $\bar{r}_{i,j}$ denotes the expected risk return for bank i and risk j over the sample T_i period. $\Delta_{i,j,t}$ denotes the deviation from risk return of bank i, risk j in period t.

Finally, we obtain a typical bank's risk returns to model marginal risk distributions. For a typical bank, its risk return is determined by market information and individual information. The market information is composed by all sample banks' deviation from risk return. Thus, by combining all sample banks' deviation from risk return and the typical bank's ($i = k$) expected risk return, we finally compute a typical bank's risk return. Specifically, the typical bank's risk return is written as

$$r_{k,j,t} = \bar{r}_{k,j} + \Delta_{j,t} = \bar{r}_{k,j} + \sum_{i} \Delta_{i,j,t} \tag{4}$$

where $r_{k,j,t}$ is the risk return of bank k, risk j in period t. $\bar{r}_{k,j}$ stands for the expected risk return of bank k and risk j. $\Delta_{j,t}$ denotes the summation of deviation from risk return of risk j in period t of all sample banks, which reflects the market information of risk j in period t.

Value-at-Risk (VaR), which has become a standard model for measuring and assessing risk is used to measure marginal risk in this paper (Huang 2013; Hsu et al. 2012). VaR is defined as a quantile of the distribution of risk returns. Thus, the larger negative value or smaller positive value of VaR corresponds to the higher level of risk (Rosenberg and Schuermann 2006). To aggregate single VaRs into total risk, we adopt the simple summation approach, which is one of the most basic and widely used risk aggregation approaches. Some risk aggregation approaches have emerged so far. Simple summation, var–covar and copula approaches are three main risk aggregation approaches. All of them have strengths and weaknesses (Li et al. 2015). Simple summation approach is one of the most basic and widely used approaches to aggregate risk (Rosenberg and Schuermann 2006; Inanoglu and Jacobs 2009; Kretzschmar et al. 2010). It has several features. One is that it is the briefest one which calculates total risk by just adding stand-alone risks. Another is that it is found to be more conservative compared with other risk aggregation approaches (Embrechts et al. 1999). Such an approach implicitly assumes that all risks are perfectly correlated, that is to say, great losses occur simultaneously, which imposes an upper bound on the true total risk (Dimakos and Aas 2004). Thus, many papers use the simple summation approach to aggregate marginal risks, such as Rosenberg and Schuermann (2006), Inanoglu and Jacobs (2009) and Kretzschmar et al. (2010). Given the purpose of our paper is to analyze the impact of OBS activities on total risk rather than risk aggregation approaches, we adopt the widely used simple summation approach to aggregate different risk types.

Besides, in the use of the simple summation approach to adding marginal risks, the marginal risk weight that represents the marginal risk contribution to total risk should also be considered. Rosenberg and Schuermann (2006) took marginal risk weights into account in the use of the simple summation approach. The total risk, which is referred as Add-VaR, is the weighted simple summation of marginal risks. The risk weight is the ratio of marginal risk exposure to the total risk exposure (the sum of all marginal risk exposures). Thus, we also use Add-VaR to measure total risk in accordance with Rosenberg and Schuermann (2006). The specific formula of Add-VaR is written as

$$Add{-}VaR_{i,t}(\alpha) = \sum_j w_{i,j,t} * VaR_{i,j}(\alpha) \tag{5}$$

and the marginal risk weight as

$$w_{i,j,t} = \left(\frac{RE_{i,j,t}}{\sum_j RE_{i,j,t}} \right) = \left(\frac{RE_{i,j,t}}{TRE_{i,t}} \right) \tag{6}$$

where $Add{-}VaR_{i,t}(\alpha)$ is the total risk in terms of return as a percent of total risk exposure for the ith bank in period t with the $(1-\alpha)$ confidence level. $VaR_{i,j}(\alpha)$ is the marginal risk of bank i and risk j under the $(1-\alpha)$ confidence level. $w_{i,j,t}$ is the marginal risk weight of bank i, risk j in period t. $TRE_{i,t}$ is the sum of different marginal risk exposures and denotes the total risk exposure.

After getting Add-VaR, which represents the loss of unit total risk exposure, we can calculate the total loss by multiplying total risk exposure and Add-VaR. The total loss represents the total risk in terms of losses. It can be written as:

$$TR_{i,t}(\alpha) = Add{-}VaR_{i,t}(\alpha) * TRE_{i,t} \tag{7}$$

where $TR_{i,t}(\alpha)$ represents the total risk in terms of losses for the ith bank in period t with the $(1-\alpha)$ confidence level.

3 Empirical analysis

3.1 Data description

Since only listed banks' financial reports are publicly available and new accounting standards were applied in 2007, we collected quarterly panel data over the period 2007–2014 from all 16 A-share listed Chinese commercial banks (Table 1) to ensure the consistency of accounts. The quarterly data of ABC and CEB from 2007 to 2009 are unavailable because they were listed in 2010. Besides, 2007-Q2 data of BOBJ, 2007-Q1 data of BONJ, BONB and CCB are also missing. Getting rid of these exceptional cases, we finally obtain 487 pieces of valid data to model individual risk distributions.

Our empirical analysis is based on quarterly data while OBS items, loan impairment loss and loan loss provision are disclosed only in annual and semi-annual financial reports. Hence, we need to make simple assumptions to obtain quarterly data of these accounts. Specifically, Q1 OBS items are equal to semi-annual OBS items and Q3 OBS items are

Table 1 The sample of all 16 listed commercial banks of china

No.	Bank	No.	Bank
1	Industrial and Commercial Bank of China (ICBC)	9	Huaxia Bank (HXB)
2	China Construction Bank (CCB)	10	Industrial Bank (IB)
3	Bank of China (BOC)	11	China Everbright Bank (CEB)
4	Agriculture Bank of China (ABC)	12	China Minsheng Bank (CMB)
5	Bank of Communications (BOCOM)	13	China CITIC Bank (CITIC)
6	China Merchants Bank (CMB)	14	Bank of Beijing (BOBJ)
7	Pingan Bank (PAB)	15	Bank of Ningbo (BONB)
8	SPD Bank (SPDB)	16	Bank of Nanjing (BONJ)

equal to annual OBS items. As for loan impairment loss, which is part of assets impairment loss, can be calculated based on known quarterly assets impairment loss. Specifically, we first calculate R, which is a ratio of loan impairment loss to assets impairment loss based on annual and semi-annual data. Then, we calculate the mean value of this ratio over the sample period ($\bar{R}$). Herein, we make a simple assumption that the quarterly R is equal to $\bar{R}$. Thus, the quarterly loan impairment loss is obtained by multiplying $\bar{R}$ and quarterly assets impairment loss. Likewise, the quarterly loan loss provision, which is determined by the quality of loans, can be obtained based on the known quarterly loans. Specifically, we define R' as the ratio of loan loss provision to loans and $\bar{R}'$ as the mean value of R' over the sample period. Thus, the quarterly loan loss provision is obtained by multiplying $\bar{R}'$ with quarterly loans based on the assumption that the quarterly R' is equal to $\bar{R}'$.

Among the sample of all 16 listed Chinese commercial banks from 2007 to 2014, the amount of financial statements data for a single bank is up to 32, which is too small to perform the empirical analysis. Thus, in order to address the problem of data shortage and provide empirical insights into the total risk of Chinese commercial banks, we construct hypothetical banks in accordance with Rosenberg and Schuermann (2006), Kretzschmar et al. (2010) and Alessandri and Drehmann (2010). In particular, we use median assets to characterize hypothetical banks and then a large hypothetical bank and a small hypothetical bank are constructed for comparison. "The big four" stated-owned banks are the four largest banks by assets in Chinese banking system. However, ABC went public relatively late so that the amount of financial statements data is relatively smaller. Thus, the asset size of the large hypothetical bank is the average of the rest three state-owned banks (ICBC, BOC and CCB). Correspondingly, the asset size of the small hypothetical bank is the average of the three smallest banks by assets (BOBJ, BONB and BONJ). By using this median approach to constructing hypothetical banks, at the end of 2014, the bank sizes in terms of risk-weighted assets for the large and small hypothetical banks are 43,462 and 2262 billion CNY, respectively.

For either of these two hypothetical banks, the amount of data is 487, which is much larger than that of a real-world bank. Furthermore, the hypothetical banks constructed by us capture the characteristics of real-world banks' asset sizes, so they are the typical banks in Chinese banking system. In a word, performing empirical analysis based on typical hypothetical banks not only addresses the problem of data shortage but also achieves general conclusions.

3.2 Empirical results

The marginal risk distribution is decided by the deviation from risk return and the expected risk return by referring to Eq. (4). The deviation from risk return, which reflects the macroeconomic background and operating conditions of the banking industry, decides the shape of marginal risk distribution. The expected risk return that reflects a bank's own features decides the horizontal axis coordinates of the marginal risk distribution. The characteristics of deviation from risk return are presented numerically in Table 2 and the shapes of marginal risk distributions are visually shown in Fig. 2.

In terms of return on risk exposure, market risk has the highest volatility (7.80%) and fattest tails (kurtosis = 60.67). The volatility (0.51%) and kurtosis (17.59) of liquidity risk come in second. The negative kurtosis present in credit risk (−1.08) and the relatively lower positive kurtosis for operational risk (3.47) suggest that credit risk and operational risk have thinner tails, with volatilities of credit and operational risks being 0.50 and 0.31%, respectively. The shape of credit risk distribution is nearly symmetric while that of other three risk types are right-skewed. Specifically, operational risk is moderately right-skewed at 1.26, liquidity risk is right-skewed at 3.14 and market risk is more significantly right-skewed at 5.71.

Table 3 reports two hypothetical banks' expected risk returns. For the large commercial bank, credit, market, liquidity and operational risk expected returns are 0.44, −9.62, −0.56 and −0.66%, respectively. The small bank's expected returns for credit (0.40%), liquidity (−0.66%) and operational (−0.76%) risks are less than those of the large bank while the expected return of market risk (−8.27%) is bigger than that of the large bank.

Since the marginal risk distribution is determined by the expected risk return and deviation from risk return, we finally get the two hypothetical banks' marginal risk distributions. The characteristics of marginal risk distributions are as illustrated in Table 4.

It is clear to see that the statistics of marginal risk distributions are of difference between the large and small banks. In particular, at 99.9% confidence level, mean values of the large bank's credit, market, liquidity and operational risks are 1.20, −0.77, 0.20 and −0.21%, respectively. For the small bank, mean values of credit, market, liquidity and operational risks are 1.15, 0.59, 0.09 and −0.31%, respectively. As for median values, the large bank's credit risk has the largest median (1.20%) while the median of operational risk (−0.21%) is between that of liquidity risk (0.16%) and market risk (−0.88%). The small bank's median of credit risk (1.16%) is still the largest while the median of market risk (0.47%) ranks latter. The smallest median is −0.32% of the operational risk and the median of liquidity risk is 0.05%.

The last four columns of Table 4 are VaR values of individual risks at different confidence levels. Since larger negative value or smaller positive value of VaR corresponds to the higher level of risk, the empirical results suggest that the large bank's market risk is higher while other three risk types (credit, liquidity and operational risks) are lower

Table 2 Descriptive statistics for deviations from risk return of four marginal risks

	Credit risk	Market risk	Liquidity risk	Operational risk
σ (%)	0.50	7.80	0.51	0.31
Skewness	0.08	5.71	3.14	1.26
Kurtosis	−1.08	60.67	17.59	3.47

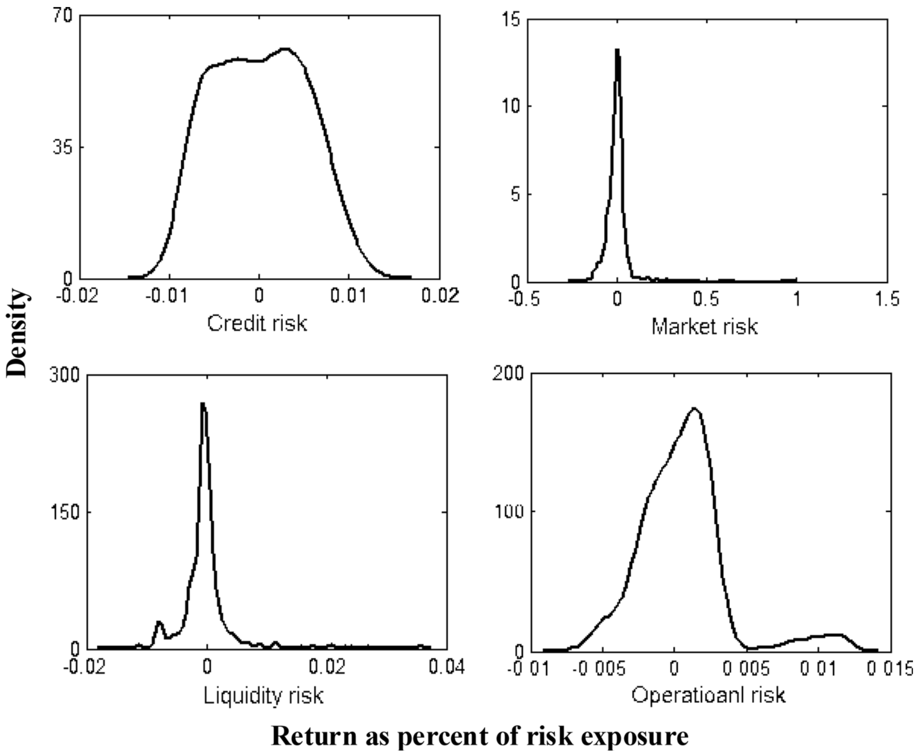

Fig. 2 Distributions of deviations from risk return of four marginal risks

Table 3 Expected risk returns of the two hypothetical banks (%)

	Large hypothetical bank				Small hypothetical bank			
	Credit risk	Market risk	Liquidity risk	Operational risk	Credit risk	Market risk	Liquidity risk	Operational risk
Expected risk returns	0.44	−9.62	−0.56	−0.66	0.40	−8.27	−0.66	−0.76

compared with the small bank. Specifically, the large bank's negative value of market risk VaR is larger than that of the small bank, so that the large bank's market risk is higher. As for liquidity risk and operational risk, the large bank's negative values of VaRs are smaller than those of the small bank. The large bank's positive value of credit risk is larger than that of the small bank. Thus, the large bank's credit, liquidity and operational risks are lower. For example, at 0.1th percentile, the large bank's market risk VaR is −25.27%, whose negative value is larger than that of the small bank (−23.92%). While the large bank's liquidity risk and operational risk VaRs are −1.47 and −0.96%, respectively, whose negative values are smaller than those of the small bank (liquidity risk: −1.58%; operational risk: −1.06%). The large bank's positive value of credit risk VaR (0.31%) is larger than that of the small bank (0.26%). Therefore, the large bank's market risk is higher while credit, liquidity and operational risks are lower compared with the small bank.

Table 4 Summary statistics of four marginal risk distributions (%)

	Large hypothetical bank				Small hypothetical bank			
	Credit risk	Market risk	Liquidity risk	Operational risk	Credit risk	Market risk	Liquidity risk	Operational risk
Mean	1.20	−0.77	0.20	−0.21	1.15	0.59	0.09	−0.31
Median	1.20	−0.88	0.16	−0.21	1.16	0.47	0.05	−0.32
0.1th percentile	0.31	−25.27	−1.47	−0.96	0.26	−23.92	−1.58	−1.06
1st percentile	0.39	−14.21	−0.68	−0.81	0.34	−12.86	−0.79	−0.92
2nd percentile	0.40	−12.51	−0.63	−0.78	0.36	−11.16	−0.74	−0.88
5th percentile	0.44	−9.62	−0.56	−0.66	0.40	−8.27	−0.66	−0.76

After getting VaR values of marginal risks, we then calculate the total risk by just adding single VaRs. According to Eq. (5), Add-VaR that is the total risk in terms of return as a percent of total risk exposure is the weighted simple summation of marginal risks. In 2014, the large bank's marginal risk weights are 44.54, 0.94, 7.96 and 46.56% for credit, market, liquidity and operational risks, respectively. The small bank's credit, market, liquidity and operational risk weights are 45.24, 0.49, 7.69 and 46.58%, respectively. Then, the total loss, which is the total risk in terms of losses, is calculated based on Eq. (7). For simplicity in what follows we shall refer to both Add-VaR and total loss as the total risk. Our quarterly financial statements data enable a quarterly view of total risk while the typical horizon of losses is 1 year. To transform the quarterly total loss into the annual total loss, we apply the *square-root-of-time rule* which is commonly used to scale an estimated quantile of a return distribution to a lower frequency T by the multiplication of $\sqrt{T}$ (Danielsson and Zigrand 2006). Table 5 gives a summary overview of the two hypothetical banks' total risks in 2014.

As shown in Table 5, there is no significant difference between Add-VaR values of these two banks while the total loss of the large commercial bank is bigger because of its larger scale. Specifically, at 99.9% confidence level, Add-VaR values of the large and small banks are −0.66 and −0.61%, respectively. The large bank may suffer an annual total loss of 578 billion CNY while the small bank's annual total loss is equal to 28 billion CNY.

Table 5 2014 Add-VaRs and total losses of the two hypothetical banks

Confidence level	Large hypothetical bank				Small hypothetical bank			
	99.9%	99%	98%	95%	99.9%	99%	98%	95%
Total risk (Add-VaR)	0.66%	−0.39%	−0.35%	0.25%	−0.61%	−0.39%	−0.36%	0.27%
Total risk (Annual losses in billion CNY)	576.68	341.58	304.48	212.96	27.71	17.82	16.24	12.06

3.3 Results analysis

3.3.1 The impact of OBS activities on the Chinese commercial bank's total risk

In this section, we empirically test whether the Chinese commercial bank's total risk is affected by OBS activities. Compared with the existing financial statements based risk aggregation framework, which only aggregates on-balance risks, our improved framework can capture both on-balance and off-balance sheet risks. Therefore, by comparing risk aggregation results estimated by these two frameworks, we first examine the overall impact of OBS activities on the bank's total risk, and then further study the individual impact of each of the OBS risk types on total risk. To our best knowledge, there are no existing studies that examine the effect of OBS activities on the Chinese commercial bank's total risk.

Although there are some studies on the correlation between banks' risks and OBS activities, there is no consensus thus far. Traditionally, OBS activities have been seen as a risk-reducing tool (Hassan et al. 1994). In contrast to findings that OBS items are negatively correlated with banks' risks, some believe that banking institutions heavily involved in OBS activities are characterized by higher risks (Calmès and Théoret 2010; Papanikolaou and Wolff 2014).

By comparing total risk with and without OBS items in 2014 (Fig. 3), we empirically prove that the risk entailed in OBS activities affects the total risk of Chinese commercial bank and the impact depends on bank size. In particular, at 99.9% confidence level, the large bank's total risk decreases from 587.12 billion CNY to 576.68 billion CNY while the small bank's total risk increases from 27.14 billion CNY to 27.71 billion CNY after taking OBS items into risk aggregation. Thus, the entire OBS activities exert a negative effect on the large bank's total risk while a positive effect on the small bank's total risk. Ignoring OBS items in risk aggregation will overestimate the large bank's total risk while the small bank's total risk will be underestimated.

The reason why the overall impact of OBS activities on the bank's total risk depends on bank size may be that the ability of OBS risk management is different between banks. OBS items have both risk-reducing as well as risk increasing attributes. The ability of OBS risk

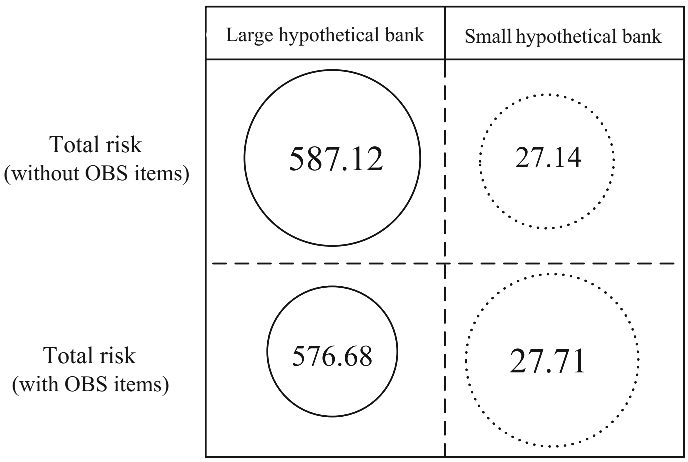

Fig. 3 Total risk with and without OBS items in 2014 (unit: billion CNY)

management determines the net impact of OBS items on bank risks (Khasawneh et al. 2012). Compared with the large bank, the small bank engages in more risky OBS activities where it lacks experience and expertise (Mercieca et al. 2007). Thus, OBS items increase the small bank's total risk while decreases the large bank's total risk. In particular, stated-owned banks play a leading role in traditional deposits and loans market. Zhao and Jian (2013) have also confirmed that the larger the bank, the stronger the ability of bank profitability. Since a keener competition leads to greater risk-taking behaviors (Hellmann et al. 2000), so the small bank engages in more risky OBS activities for pursuing higher profit. For example, the use of OBS derivatives as speculation rather than hedging tools increases the riskiness of the small bank. Furthermore, limited knowledge on markets and OBS transactions hampers the small bank's performance. Therefore, OBS items are negatively linked to the Chinese large bank's total risk while positively linked to the small bank's total risk.

However, the findings in Fig. 3 also reveal that the gap between total risk with and without OBS items is not obvious, which weakens the need of incorporating OBS items into risk aggregation framework. Thus, we then explain why the difference caused by OBS items in risk aggregation is not apparent. To show the change of total risk brought about by OBS activities, we compute a change rate that is the proportional change of total risk ($\Delta TR\%$) using total risk with OBS activities (TR_{OBS}) versus total risk without OBS activities (TR):$(TR_{OBS} - TR)/TR$.

According to Eq. (7), total risk is the product of Add-VaR and total risk exposure. Consequently, the specific equation for the change rate of total risk after considering OBS items can be written as

$$\begin{aligned}
\Delta TR\% &= \Delta TR/TR = (TR_{OBS} - TR)/TR \\
&= [TRE_{OBS} * (Add{-}VaR_{OBS}) - TRE * (Add{-}VaR)]/TR \\
&= \{TRE * (1 + \Delta TRE\%) * (Add{-}VaR)[1 + \Delta(Add{-}VaR)\%] - TRE * (Add{-}VaR)\}/TR \\
&= \{TRE * (Add{-}VaR) * [(1 + \Delta TRE\%) * (1 + \Delta(Add{-}VaR)\%) - 1]\}/TR \\
&= TR * [(1 + \Delta TRE\%) * (1 + \Delta(Add{-}VaR)\%) - 1]/TR \\
&= (1 + \Delta TRE\%) * (1 + \Delta(Add{-}VaR)\%) - 1
\end{aligned} \tag{8}$$

where $\Delta TR\%$, $\Delta TRE\%$ and $\Delta(Add{-}VaR)\%$ are the change rate of total risk, total risk exposure and Add-VaR, respectively. After incorporating OBS activities into risk aggregation, the total risk exposure will increase while Add-VaR will decrease. Thus, $\Delta TRE\%$ is the positive value while $\Delta(Add{-}VaR)\%$ is the negative value. With larger absolute values of $\Delta TRE\%$ and $\Delta(Add - VaR)\%$, the absolute value of $\Delta TR\%$ will become larger. For example, $\Delta TR\%$ is equal to -1% if $\Delta TRE\%$ is 10% and $\Delta(Add{-}VaR)\%$ is -10%. However, if $\Delta TRE\%$ increases to 40% and $\Delta(Add{-}VaR)\%$ decreases to -40%, $\Delta TR\%$ is equal to -16%.

Figure 4 visually shows the change rates of total risk exposure, Add-VaR and total risk after incorporating OBS activities into risk aggregation. It is clear to see that change rate of total risk is unapparent. Specifically, the large bank's total risk declines by 2.25% while the small bank's total risk increases by 2.59%. According to Eq. (8), the unapparent change rate of total risk is caused by smaller absolute values of $\Delta TRE\%$ and $\Delta(Add{-}VaR)\%$. There are two reasons why the absolute values of $\Delta TRE\%$ and $\Delta(Add{-}VaR)\%$ are smaller. One is that only a part of OBS items is taken into risk measurement. Another is that the

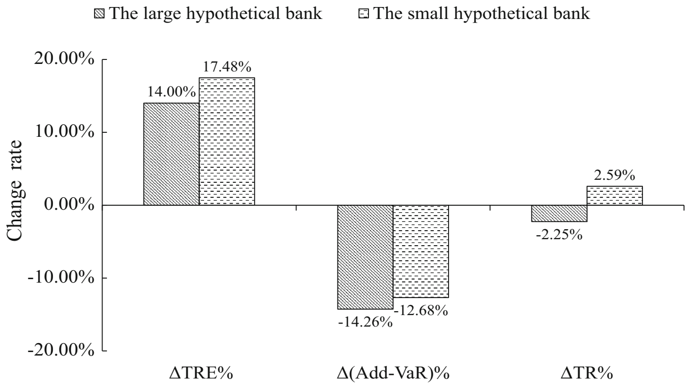

Fig. 4 The change rates caused by incorporating OBS items into risk aggregation

current scale of Chinese banks' OBS activities is still small compared with western countries' banks.

Based on available data, the OBS items we consider in risk aggregation account for 15.41 and 19.21% of total on-balance sheet assets for the large bank and small bank, respectively. But according to the *China Financial Stability Report 2015*, at the end of 2014, OBS items accounted for 40.87% of total on-balance sheet assets. Therefore, the absolute values of $\Delta TRE\%$ and $\Delta(Add{-}VaR)\%$ will get larger after considering all of the OBS items.

In addition, the continuous growth of OBS activities in Chinese banking system will enlarge the absolute values of $\Delta TRE\%$ and $\Delta(Add{-}VaR)\%$. According to the *China Financial Stability Report 2015*, OBS items of Chinese banking system continued to rise over the period 2010–2014 (Fig. 5). Specifically, OBS activities of Chinese banks increased from 33 trillion CNY to 70 trillion CNY and the percentage of OBS items accounted for total balance sheet assets increased from 35 to 41%. However, compared with OBS items in American banks, whose ratio of OBS items to total balance assets rose from 78 to 142.9% over the period 1983–1986, OBS items in Chinese banking sector have a huge space for development.

All in all, the increasingly standardized disclosure requirements for OBS items and the continuous growth of OBS activities in Chinese banking system will enlarge the changes of total risk exposure and Add-VaR after taking OBS items into risk aggregation, which further result in a more apparent difference between total risk with and without OBS items. Thus, incorporating OBS items into risk aggregation framework is reasonable and necessary.

Besides empirically testing the overall impact of OBS activities on the bank's total risk, we examine the individual impact of each of the OBS risk types on total risk by incorporating OBS risk types into risk aggregation one by one. As noted in Sect. 2.2, the improved risk aggregation framework only adds OBS credit risk and operational risk. The results of individual impact on total risk of each of the OBS risk types are shown in Fig. 6.

Figure 6 shows the change rates of bank risks after incorporating OBS risk types into risk aggregation. As noted above, the change rate is a ratio of the difference between bank risk with and without OBS risk types to bank risk without OBS risk types, which is the proportional change of bank risk due to OBS risks. The positive value of the change rate indicates that bank risk increases while the negative value indicates that bank risk

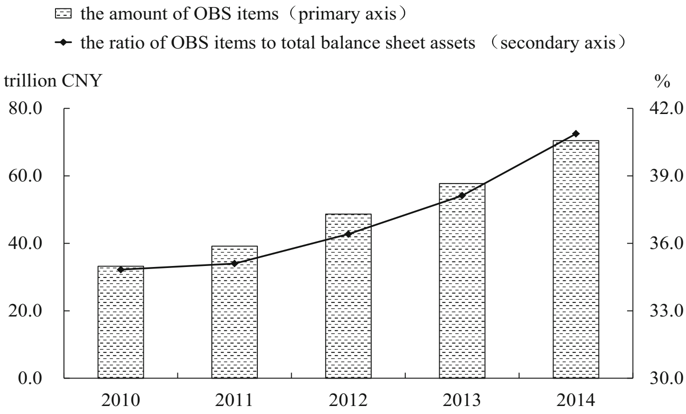

Fig. 5 The growth of Chinese banking OBS activities

decreases after considering OBS items. As shown in Fig. 6, OBS credit risk is positively related to total risk while OBS operational risk is negatively related to total risk for both large and small banks. In particular, after incorporating OBS credit risk into risk aggregation, the increase rates of credit risk for large and small hypothetical banks are 4.30 and 15.99%, respectively. Then the increase of credit risk leads to higher total risk. Total risks for the large and small banks increase by 0.91 and 3.78%, respectively. After incorporating OBS operational risk into risk aggregation, the decrease rates of operational risk for large and small hypothetical banks are −3.92 and −2.00%, respectively. Then the decrease of operational risk leads to lower total risk. Total risks for the large and small banks decrease by 2.69 and 1.68%, respectively. Finally, by incorporating OBS all risk types into risk aggregation, the total risk of large hypothetical bank decreases by 2.25% while the total risk of small hypothetical bank increases by 2.59%.

Then we give some reasons to explain why OBS credit risk is positively related to total risk while OBS operational risk is negatively related to total risk for both large and small banks. Specifically, since the on-balance sheet credit scale has been constrained by regulatory agencies, banks develop OBS credit commitments that are not registered on banks'

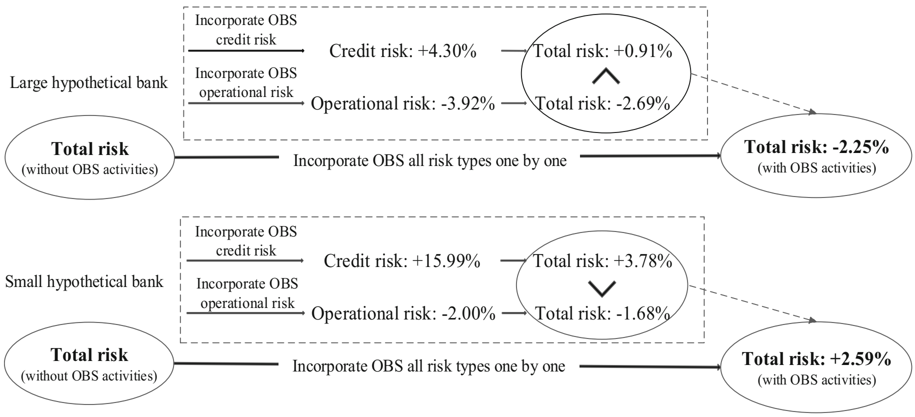

Fig. 6 The change rates of bank risks caused by considering each of the OBS risk types

balance sheet to grant more loans (Boyd and Gertle 1994). Credit losses on OBS credit risk exposures make banks actually take more credit risk (Avery and Berger 1991; Demsetz and Strahan 1997). The increase in credit risk further leads to the higher total risk. Therefore, OBS credit risk is positively related to a bank's total risk. Rosenberg and Schuermann (2006) deem that all assets are in some way subject to operational risk. Thus, OBS operational risk exposures include all OBS activities in this paper. An incentive to develop OBS activities is to increase fee and commission income (DeYoung and Rice 2004). Since we map fee and commission income into operational risk profit and loss (Kuritzkes and Schuermann 2007), the addition of fee and commission income from OBS operational risk activities will increase operational risk return and finally reduce operational risk. Then the decrease in operational risk reduces the total risk. Thus, OBS operational risk is negatively related to total risk.

Although OBS credit risk is positively linked to total risk while OBS operational risk is negatively linked to total risk for both large and small banks, the influence degrees of each of the OBS risk types on total risk differ by banks. Compared with the large bank, the small bank is greatly affected by the OBS credit risk while slightly affected by the OBS operational risk. Thus, by comparing the different influence degrees of each of the OBS risk types on total risk, we can explain why the overall impact of OBS activities on total risk (Fig. 4) depends on bank size. Specifically, for the large bank's total risk, the negative effect of OBS operational risk (−2.69%) is larger than the positive effect of OBS credit risk (+0.91%). Thus, after considering all OBS activities into risk aggregation, the total risk of the large bank decreases (−2.25%). As for the small bank's total risk, the positive effect of OBS credit risk (+3.78%) is larger than the negative effect of the OBS operational risk (−1.68%). Thus, after considering all OBS activities into risk aggregation, the total risk of the small bank increases (+2.59%).

To summarize, OBS credit risk is positively related to total risk while OBS operational risk is negatively related to total risk for both large and small banks. However, the influence degrees of each of the OBS risk types on total risk differ by banks, which further lead to the overall impact of OBS activities on the bank's total risk depends on bank size. Specifically, the entire OBS activities are negatively related with the large bank's total risk while positively related with the small bank's total risk.

3.3.2 The transformation of Chinese banks' risks during and after the subprime crisis

After obtaining total risks of Chinese commercial banks, in the following text, we further study how Chinese banks' risks are affected by the subprime crisis. Indeed, some studies have found that the financial crisis affected the bank risk-taking behavior and bank risks were related to the phase of the business cycle (Delis and Kouretas 2011; Shim 2013). Therefore, in this paper, we study how the subprime crisis affected Chinese commercial banks' risks by dividing the entire sample into two subsets, during and after the subprime crisis. In accordance with Zhu et al. (2015), the subprime crisis began at 2007-Q4 and ended at 2011-Q3.

As illustrated in Fig. 7, the total risk (Add-VaR at 99.9% confidence level) is significantly larger during times of crisis for both large and small banks. Just like most banks across the world which had plunged into severe risk (Dias and Ramos 2014), Chinese commercial banks had higher risks during the subprime crisis.

To further study why total risk became larger when the subprime crisis broke out, we analyze risk weights and marginal risks because the total risk is decided by both of them [following Eq. (5)]. Figure 8 visually shows that the marginal risk weights almost remain

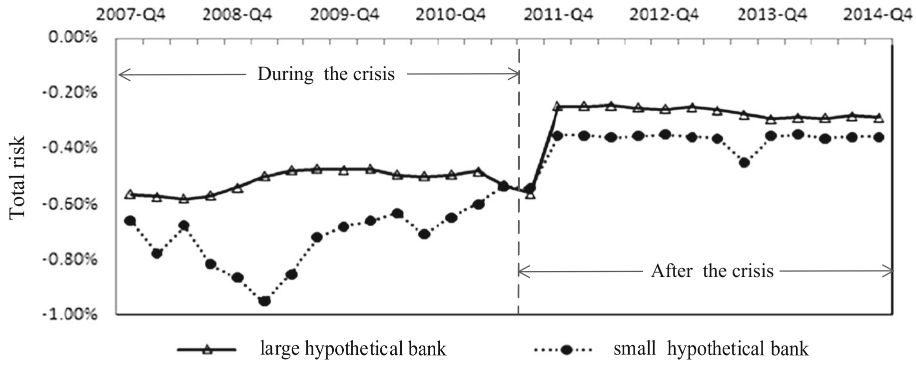

Fig. 7 The changes of total risks of Chinese commercial banks during and after the subprime crisis. The larger negative value corresponds to the higher level of total risk

unchanged. Or,in other words, the outbreak of the subprime crisis did not significantly affect the business mix of Chinese commercial banks. Thus, the change of marginal risk weights is not the main cause for larger total risk during the crisis. Then, we show the changes in four marginal risks of Chinese commercial banks during and after the crisis in Fig. 9. As noted above, the larger negative value or smaller positive value corresponds to higher marginal risk. It is clear that for both large and small banks, market and liquidity risks experienced a sharp increase while changes in credit and operational risks were not obvious with the outbreak of the subprime crisis. The VaR values of marginal risks reported in Table 6 also support this finding precisely.

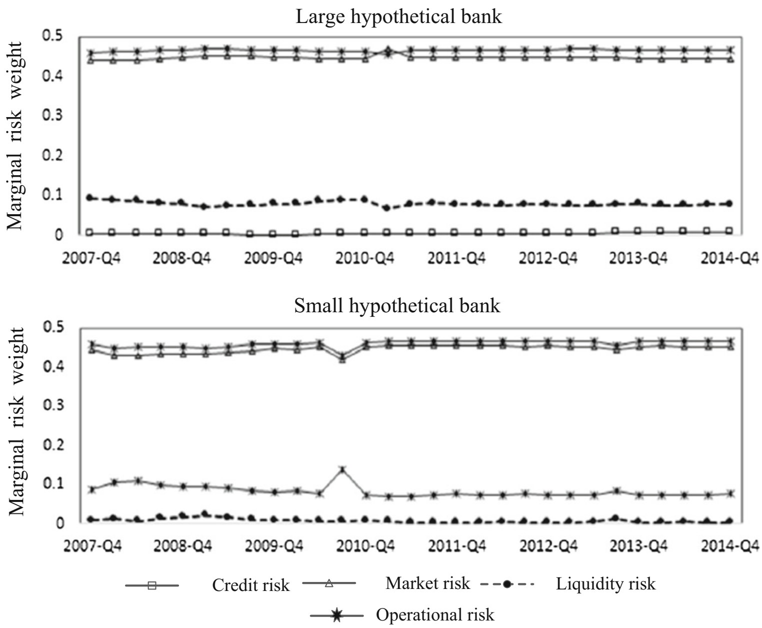

Fig. 8 The four marginal risk weights during and after the crisis

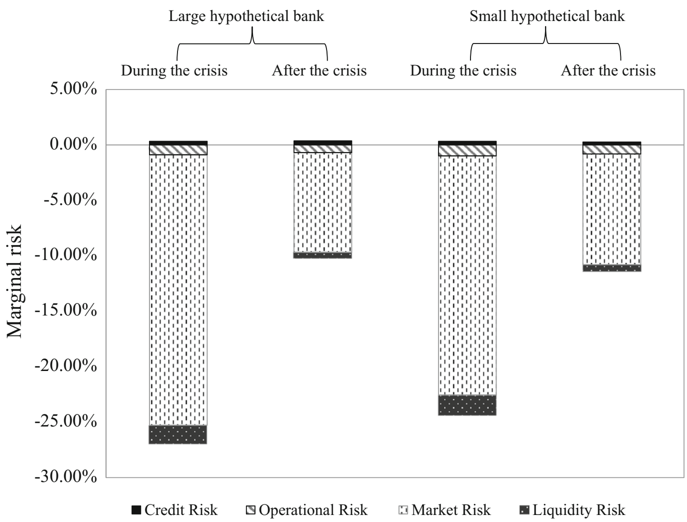

Fig. 9 The changes in four marginal risks of Chinese commercial banks during and after the subprime crisis. The larger negative value corresponds to the higher level of marginal risk

Table 6 The comparison of marginal risks during and after the subprime crisis

Marginal risk (99.9% VaR)	Large hypothetical bank		Small hypothetical bank	
	During the crisis (%)	After the crisis (%)	During the crisis (%)	After the crisis (%)
Credit risk	0.32	0.37	0.33	0.26
Operational risk	−0.88	−0.69	−0.98	−0.82
Market risk	−24.39	−9.00	−21.55	−9.99
Liquidity risk	−1.63	−0.54	−1.81	−0.60

Table 6 reports VaR values of marginal risks at 99.9% confidence level during and after the subprime crisis. For both large and small banks, there are slight changes in VaR values of credit and operational risks while significant changes in VaR values of market and liquidity risks. In particular, when the subprime crisis broke out, the large bank's credit risk VaR slightly decreased from 0.37 to 0.32% and operational risk VaR experienced a modest reduction from −0.69 to −0.88%. It is important, however, to note that market risk VaR drastically dropped from −9.00 to −24.39% and liquidity risk VaR substantially dropped from −0.54 to −1.63%. As for the small bank, credit risk and operational risk changed slightly, with VaR values of credit risk and operational risk being 0.33 and −0.98% during the crisis and 0.26 and −0.82% after the crisis, respectively. However, the small bank's market risk VaR substantially dropped from −9.99 to −21.55% and liquidity risk VaR decreased from −0.60 to −1.81% with the outbreak of the subprime crisis.

Therefore, we can conclude that the significant increase of liquidity risk and market risk is the main cause for the larger total risk during the subprime crisis. Furthermore, our empirical results are consistent with findings in Alexander et al. (2013) and Cornett et al. (2011). Alexander et al. (2013) found that banks across the world suffered vast trading losses during the subprime crisis. Cornett et al. (2011) concluded that liquidity dried up during the bad years of 2007–2009 and liquidity risk was a challenge to a bank in times of stress.

4 Conclusion

In this paper, we improve the financial statements based risk aggregation framework by incorporating OBS activities into risk aggregation, which allows us to capture both on-balance and off-balance sheet risks simultaneously. In the empirical analysis, we apply this improved framework to aggregate credit, market, liquidity and operational risks by using a sample of all 16 Chinese listed commercial banks for the period 2007–2014. Then we empirically study whether the overall impact of OBS activities and the individual impact of each of the OBS risk types on total risk depend on bank size by constructing two typical Chinese commercial banks. Moreover, this research divides the samples into two subsets to find out the transformation of Chinese banks' risks during and after the subprime crisis.

Our empirical results show that the total risk of Chinese commercial banks is affected by OBS activities. Specifically, OBS credit risk is positively linked to total risk while OBS operational risk is negatively linked to total risk for both large and small banks. However, the influence degrees of each of the OBS risk types on total risk differ by banks, which further lead to the conclusion that the overall impact of OBS activities on total risk depends upon bank size. Specifically, the entire OBS activities are negatively related with the large bank's total risk while positively related with the small bank's total risk. Hence, the large bank's total risk is overestimated while the small bank's total risk is underestimated if OBS items are ignored in risk aggregation. Besides, the risk transformation analysis for Chinese commercial banks suggests that it is the increase of liquidity risk and market risk that leads to the larger total risks for both large and small banks during the subprime crisis.

However, this study has several limitations. First, the difference between total risk with and without OBS items is not obvious. However, the development of OBS activities and the increasingly standardized disclosure requirements for OBS items will enlarge the deviation if OBS items are ignored in risk aggregation. Second, the correspondence between risk types and financial statements is kind of rough. For example, net interest income bears credit risk and market risk simultaneously. And whether all assets are subject to operational risk is still open to question. In future studies, employment of other information may help calibrate the corresponding relationship to some extent.

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References

Acerbi C, Scandolo G (2008) Liquidity risk theory and coherent measures of risk. Quant Finance 8(7):681–692. doi:10.1080/14697680802373975

Acharya VV, Richardson M (2009) Causes of the financial crisis. Crit Rev 21(2–3):195–210. doi:10.1080/08913810902952903

Alessandri P, Drehmann M (2010) An economic capital model integrating credit and interest rate risk in the banking book. J Bank Finance 34(4):730–742. doi:10.1016/j.jbankfin.2009.06.012

Alexander GJ, Baptista AM, Yan S (2013) A comparison of the original and revised Basel market risk frameworks for regulating bank capital. J Econ Behav Organ 85:249–268. doi:10.1016/j.jebo.2012.04.007

Avery RB, Berger AN (1991) Loan commitments and bank risk exposure. J Bank Finance 15(1):173–192. doi:10.1016/0378-4266(91)90045-N

Bae KH, Tan H, Welker M (2008) International GAAP differences: the impact on foreign analysts. Account Rev 83(3):593–628. doi:10.2308/accr.2008.83.3.593

Basel Committee on Banking Supervision (1986) The management of banks' off-balance sheet activities exposures. Bank for International Settlements, Basel

Basel Committee on Banking Supervision (1988) International convergence of capital measurement and capital standards. Bank for International Settlements, Basel

Basel Committee on Banking Supervision (1996) Amendment to the capital accord to incorporate market risks. Bank for International Settlements, Basel

Basel Committee on Banking Supervision (2003) Trends in risk integration and aggregation. Bank for International Settlements, Basel

Basel Committee on Banking Supervision (2006) International convergence of capital measurement and capital standards: a revised framework. Bank for International Settlements, Basel

Basel Committee on Banking Supervision (2008) Principles for sound liquidity risk management and supervision. Bank for International Settlements, Basel

Basel Committee on Banking Supervision (2010) Basel III: a global regulatory framework for more resilient banks and banking systems. Bank for International Settlements, Basel

Blundell-Wignall A, Atkinson P (2010) Thinking beyond Basel III. OECD J Financ Mark Trends 2010(1):9–33. doi:10.1787/fmt-2010-5km7k9tpcjmn

Boyd JH, Gertle M (1994) Are banks dead? Or are the reports greatly exaggerated?. Quarterly Review, Federal Reserve Bank of Minneapolis

Brunnermeier MK (2009) Deciphering the liquidity and credit crunch 2007–2008. J Econ Perspect 23(1):77–100. doi:10.1257/jep.23.1.77

Calmès C, Théoret R (2010) The impact of off-balance-sheet activities on banks returns: an application of the ARCH-M to Canadian data. J Bank Finance 34(7):1719–1728. doi:10.1016/j.jbankfin.2010.03.017

Chateau JPD (2009) Marking-to-model credit and operational risks of loan commitments: a Basel-2 advanced internal ratings-based approach. Int Rev Financ Anal 18(5):260–270. doi:10.1016/j.irfa.2009.07.001

Chavez-Demoulin V, Embrechts P, Nešlehová J (2006) Quantitative models for operational risk: extremes, dependence and aggregation. J Bank Finance 30(10):2635–2658. doi:10.1016/j.jbankfin.2005.11.008

Cornett MM, McNutt JJ, Strahan PE, Tehranian H (2011) Liquidity risk management and credit supply in the financial crisis. J Financ Econ 101(2):297–312. doi:10.1016/j.jfineco.2011.03.001

Danielsson J, Zigrand JP (2006) On time-scaling of risk and the square-root-of-time rule. J Bank Finance 30(10):2701–2713. doi:10.1016/j.jbankfin.2005.10.002

Delis MD, Kouretas GP (2011) Interest rates and bank risk-taking. J Bank Finance 35(4):840–855. doi:10.1016/j.jbankfin.2010.09.032

Demsetz RS, Strahan PE (1997) Diversification, size, and risk at bank holding companies. J Money Credit Bank 29(3):300–313. doi:10.2307/2953695

DeYoung R, Rice T (2004) Noninterest income and financial performance at U.S. commercial banks. Financ Rev 39(1):101–127. doi:10.1111/j.0732-8516.2004.00069.x

Dias JG, Ramos SB (2014) The aftermath of the subprime crisis: a clustering analysis of world banking sector. Rev Quant Financ Acc 42(2):293–308. doi:10.1007/s11156-013-0342-3

Dimakos XK, Aas K (2004) Integrated risk modelling. Stat Modelling 4(4):265–277. doi:10.1191/1471082X04st079oa

Drehmann M, Sorensen S, Stringa M (2010) The integrated impact of credit and interest rate risk on banks: a dynamic framework and stress testing application. J Bank Finance 34(4):713–729. doi:10.1016/j.jbankfin.2009.06.009

Embrechts P, McNeil AJ, Straumann D (1999) Correlation: pitfalls and alternatives. Risk 12:69–71

Hassan MK, Karels GV, Peterson MO (1994) Deposit insurance, market discipline and off balance sheet banking risk of large U.S. commercial banks. J Bank Finance 18(3):575–593. doi:10.1016/0378-4266(94)90010-8

Hellmann TF, Murdock KC, Stiglitz JE (2000) Liberalization, moral hazard, in banking and prudential regulation: are capital requirements enough? Am Econ Rev 90:147–165. doi:10.1257/aer.90.1.147

Hou X, Wang Q, Li C (2015) Role of off-balance sheet operations on bank scale economies: evidence from China's banking sector. Emerg Mark Rev 22:140–153. doi:10.1016/j.ememar.2014.10.001

Hsu CP, Huang CW, Chiou WJP (2012) Effectiveness of copula-extreme value theory in estimating value-at-risk: empirical evidence from Asian emerging markets. Rev Quant Financ Acc 39(4):447–468. doi:10.1007/s11156-012-0283-2

Huang AYH (2013) Value at risk estimation by quantile regression and kernel estimator. Rev Quant Financ Acc 41(2):225–251. doi:10.1007/s11156-012-0308-x

Inanoglu H, Jacobs M (2009) Models for risk aggregation and sensitivity analysis: an application to bank economic capital. J Risk Financ Manag 2(1):118–189. doi:10.3390/jrfm2010118

Karim D, Liadze I, Barrell R, Davis EP (2013) Off-balance sheet exposures and banking crises in OECD countries. J Financ Stab 9(4):673–681. doi:10.1016/j.jfs.2012.07.001

Khasawneh AY, Khrawish HA, Khrisat FA (2012) The determinants of OBS activities in Jordan banking system: panel data analysis. Eur J Econ Finance Adm Sci 47:30–42

Kretzschmar G, McNeil AJ, Kirchner A (2010) Integrated models of capital adequacy—why banks are undercapitalized. J Bank Finance 34(12):2838–2850. doi:10.1016/j.jbankfin.2010.02.028

Kuritzkes A, Schuermann T (2007) What we know, don't know and can't know about bank risk: a view from the trenches. The known the unknown and the unknowable in financial risk management. Princeton University Press, Princeton

Kwak W, Lee HY, Eldridge SW (2009) Earnings management by Japanese bank managers using discretionary loan loss provisions. Rev Pac Basin Financ Mark Policies 12(01):1–26. doi:10.1142/S0219091509001526

Li J, Yi S, Zhu X, Feng J (2012) Mutual information based copulas to aggregate banking risks. In: 2012 fifth international conference on business intelligence and financial engineering, Lanzhou

Li J, Zhu X, Chen J, Gao L, Feng J, Wu D, Sun X (2014) Operational risk aggregation across business lines based on frequency dependence and loss dependence. Math Probl Eng 2014:404208. doi:10.1155/2014/404208

Li J, Zhu X, Lee CF, Wu D, Feng J, Shi Y (2015) On the aggregation of credit, market and operational risks. Rev Quant Financ Acc 44(1):161–189. doi:10.1007/s11156-013-0426-0

Mercieca S, Schaeck K, Wolfe S (2007) Small European banks: benefits from diversification? J Bank Finance 31(7):1975–1998. doi:10.1016/j.jbankfin.2007.01.004

Mustika G, Suryatinc E, Hall MJB, Simper R (2015) Did Bank Indonesia cause the credit crunch of 2006–2008? Rev Quant Financ Acc 44(2):269–298. doi:10.1007/s11156-013-0406-4

Papanikolaou NI, Wolff CCP (2014) The role of on-and off-balance-sheet leverage of banks in the late 2000s crisis. J Financ Stab 14:3–22. doi:10.1016/j.jfs.2013.12.003

Rajan RG (2006) Has finance made the world riskier? Eur Financ Manag 12(4):499–533. doi:10.1111/j.1468-036X.2006.00330.x

Rosenberg JV, Schuermann TA (2006) General approach to integrated risk management with skewed, fat-tailed risks. J Financ Econ 79(3):569–614. doi:10.1016/j.jfineco.2005.03.001

Saito Y (2012) The demand for accounting information: young NASDAQ listings versus S&P 500 NYSE listings. Rev Quant Financ Acc 38(2):149–175. doi:10.1007/s11156-010-0223-y

Seow GS, Tam K (2002) The usefulness of derivative-related accounting disclosures. Rev Quant Financ Acc 18(3):273–291. doi:10.1023/A:1015392302022

Shim J (2013) Bank capital buffer and portfolio risk: the influence of business cycle and revenue diversification. J Bank Finance 37(3):761–772. doi:10.1016/j.jbankfin.2012.10.002

Zhao S, Jian J (2013) Size does matter for profitability! Testing economies of scale in Chinese banking industry. J Appl Sci 13(17):3510. doi:10.3923/jas.2013.3510.3515

Zhu X, Xie Y, Li J, Chen J, Yang S, Sun X, Wu D (2015) Change point detection for subprime crisis in american banking: from the perspective of risk dependence. Int Rev Econ Finance 38:18–28. doi:10.1016/j.iref.2014.12.011