EVALUATING OFF-BALANCE SHEET EXPOSURES IN BANKING CRISIS DETERMINATION MODELS

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Abstract: Given the evident effect that banks' off-balance sheet activity has had on systemic vulnerability in the sub-prime crisis, we test for a consistent impact of off-balance sheet exposures on the probability of banking crises in OECD countries since 1980. Variables capturing off-balance sheet activity have been neglected in most early warning models to date, mainly due to the lack of the data. We find that the change in a proxy of off-balance sheet activity of banks derived from the share of non-interest income is significant in a parsimonious logit model also featuring bank capital adequacy, liquidity, changes in house prices and the current account balance to GDP ratio. We consider it essential that regulators take into account the results for the above proxy in regulating off-balance sheet exposures and controlling their contribution to systemic risk.

Keywords: Banking crises, logit, off-balance sheet activity
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1 Introduction

Public commentary on the recent sub-prime crisis has repeatedly highlighted the role of banks' off-balance sheet (henceforth OBS) activities. Figures highlighting the exposure of banks to OBS risks have been widely cited[2]. Structured investment vehicle (SIVs) and conduits, for example, were often lightly regulated with little capital cover, and the authorities were in some cases surprised by the volume of such activity that came to light in the crisis (Davis 2009). Academic commentators have started to focus on the design of banks' OBS vehicles, but to our knowledge there are no formal systematic cross country empirical investigations of their contribution to financial crises. We suggest the dearth of empirical work arises largely from a paucity of data and not from a lack of underlying justification. Indeed, both banking theory and the major impact OBS activities have had on banks' profits argue for a major effort to be made with research.

Accordingly, in this paper, we investigate the effect of off-balance sheet activity on banks' vulnerability to crises. First, we briefly provide a theoretical justification for research into off-balance sheet activity, and then based on recent work by Barrell et al (2010) illustrate that alongside regulatory variables such as leverage and liquidity ratios and macro indicators such as the change in house prices and current account balance to GDP ratio, the change in the ratio of off-balance sheet to on-balance sheet activity plays a significant role in predicting banking crises.

The paper is structured as follows. In Section 2, we provide some background and give an overview of the literature concerning the off-balance sheet exposures in OECD country banking crises generally. In Section 3 we go through methodologies for constructing a variable proxying off-balance sheet activity. Section 4 covers the estimation and analyzes the results. Section 5 briefly assesses policy implications and Section 6 concludes.

2 Background and literature

The key difficulty for researchers in this area is finding appropriate data or estimates of OBS. An early attempt to resolve these issues was Boyd and Gertler (1994), who investigated the claim that the role of bank intermediation in credit allocation had declined in the US. They found that such claims were made on the basis of standard measures of banking activity (such as the ratio of bank assets to total credit or bank credit to GDP). These measures did not take into account banks' securitizations and other off-balance sheet and non-interest activities (which also include loan sales, backup lines of credit, and risk sharing through derivatives). The process involved is often referred to as the unbundling of intermediation. Other key forms of non-interest income are profits on proprietary trading, fees and service charges on deposits, securities underwriting fees and commissions on brokered securities transactions for third parties. Technical change, deregulation, globalization, increased and transformed wealth of individuals and increased competition are factors that underlie these shifts, as well as historically lower capital adequacy requirements for off-balance sheet activities, see also Davis and Tuori (2000).

We note in this context that whereas it is traditionally considered that fees and charges are non-risky forms of non-interest activity, this is not the case if the demand for these services is

[2] See for example,
http://articles.moneycentral.msn.com/Investing/ContrarianChronicles/BanksDarkOffBalanceSheetWorld.aspx, http://blogs.reuters.com/rolfe-winkler/2009/09/17/ending-the-off-balance-sheet-charade/ and http://www.bloomberg.com/apps/news?pid=20601110&sid=akv_p6LBNIdw.

highly volatile, or the bank faces reputation risk across its whole range of activities if it runs such business lines badly.

Boyd and Gertler took into account the shift of commercial banking towards OBS activities and showed that the declining role of US banks was no longer apparent in their estimates. They used the rate of return for on-balance sheet assets to derive a measure of OBS assets according to the scale of non-interest income. It was assumed that non-interest income was generated by implicit off-balance sheet assets with the same risk and return characteristics as that of on-balance sheet activity as indicated by net interest income. The authors note that a similar form of capitalization of certain OBS activities that entailed risk exposure was required under Basel 1 for capital adequacy purposes, to provide credit equivalents. More details of the methodology are provided in Appendix 2.

The pattern of growing non-interest income and its implications for intermediation were also noted by Rogers (1998), who pointed out that from the late 1960s onwards, US banks had reduced their reliance on interest income from traditional activities. Instead, they placed increasing importance on the fee-based incomes they generated from securitization. Davis and Tuori (2000) found similar patterns in Europe.

Recently Acharya and Richardson (2009) noted that the move towards securitization-generated income was a feature that characterized the market-based banking systems of several OECD economies. They argue that the post-2000 explosion of asset backed security (ABS) issuance was driven by banks' desire to avoid holding costly capital against their assets. One way banks did this was by removing assets off the balance sheet by holding asset backed securities in SIVs and conduits, for which banks then guaranteed the asset backed commercial paper financing. The other was holding other banks' AAA ABS tranches on-balance sheet. The authors suggest that this regulatory arbitrage was the main cause of the sub-prime episode. Only the on-balance sheet form of regulatory arbitrage will be captured by conventional measures of capital-assets ratios, and even there, a leverage based measure rather than a risk-based capital adequacy measure would best have indicated the risks.

The increase in OBS throughout many banking systems may be due to banks' desire to mimic the business strategies of their peers. Farhi and Tirole (2009) suggest that the maturity mismatch within SIVs and conduits (between long-term mortgage backed assets and the short term commercial paper used to finance them) was a structural feature of the business models of most banks who displayed strategic complementarities with their peers. When authorities use monetary policy to bail out failing banks, society incurs a fixed cost which is only justified if sufficient banks need bailing out. Therefore each individual bank correlates its risk exposure with other banks, such that OBS risks can become systemically high.

Finally, Feldman and Lueck (2007) replicated the Boyd-Gertler calculations for US data up to 2006. They found that capitalizing non-interest income gave a roughly constant share of banks in total intermediation. They noted limitations to the Boyd-Gertler approach, notably the assumption that banks generate equal profitability from on and off-balance sheet activity, but nonetheless found it plausible. Clearly, if banks are more competitive in traditional lending than in non-interest generation,[3] the latter could include a wider margin and hence OBS could be overestimated. Meanwhile conclusions about banks' overall share of intermediation cannot be drawn without allowing for the non-interest activity of non-banks

[3] De Bandt and Davis (2000) in a study of the competitiveness of banking systems, found that the competitive position for interest generating and non-interest generating activities varied between countries. In the US non-interest income was found to be a more competitive market than interest income, while in France the opposite was true. In Germany and Italy positions were comparable.

for which data are not generally available. However, the method should capture trends in OBS even if the scale of activity is not correctly measured, and it is these trends that are central to our argument below. We present an estimate of the share of on balance sheet assets in the total balance sheet including an imputed off balance sheet, in an appendix 9.

As the recent crisis has shown, capital adequacy and liquidity ratios that did not take into account the riskiness of OBS activities proved to be misleading. Whereas banks may have appeared healthy and compliant with regulatory rules, they were in fact weak due to the undercapitalization of OBS activity. Accordingly, our aim is to take into account the degree of overall OBS activity by banks and its impact on systemic risk. The first step is to estimate the amount of OBS activity by the banking system of each sample country.

3 Methodology and Data for Estimating Implicit OBS Activities

In this section, we outline our methodology used to arrive at the measure of banks' OBS activity at an aggregate level. On-balance sheet income comes from interest paid on loans made less provisions on those loans and interest paid on the on balance deposits (and other non-equity liabilities). Off-balance sheet income is more varied in its nature, as noted in Section 2 above. Following our earlier work (Barrell et al 2010), our aim was to cover the banking sectors of 14 OECD countries, namely Belgium, Canada, Denmark, Finland, France, Germany, Italy, Japan, Netherlands, Norway, Spain, Sweden, the UK and the US. We then use a measure of OBS in logit models of banking crises, as detailed below.

Since attempts to measure the scale of OBS assets from banks' financial statements proved abortive[4], we investigated the indirect approach of Boyd and Gertler (1994) who had already estimated US banks OBS assets over the period 1961 – 1993. This approach was subsequently updated by Feldman and Lueck (2007). Boyd and Gertler (1994) assumed that most non-interest income is generated by securitizations and similar forms of assets that are stored off-balance sheet, and that the return on assets on- and off-balance sheet are equal. These assumptions allow us to capitalize non-interest income using the balance sheet return in order to derive an estimate of OBS assets:

$$A_o = A_b\,[Y/(I - E - P_b)] \qquad (1)$$

where A_b denotes on-balance sheet assets, A_o – implicit off-balance sheet assets, Y is non-interest income, I - interest income, E - interest expenses and P_b is the share of provisions allocated to the loan book. The details of the Boyd and Gertler (1994) approach and calculations are given in Appendix 2.

All variables listed in the equation (1) can be found in (or derived from) profit and loss statements. Our approach differs from that of Boyd and Gertler in that we have to include fee income in our measure of OBS activity, whereas Boyd and Gertler adjust OBS activity down for fee-based off-balance sheet activities by assuming all OBS in 1961-70 were such trust-type activities and service charges on deposits, and that the ratio of this income to on balance sheet income stayed constant. Their implicit assumption is that such fee based OBS activity is "non-risky". We did not have scope to make this latter adjustment, and have generated a series reported below which includes fee income generating activities on the same basis as other OBS activity. However, as noted above, we contend that fee based income is far from

[4] The "Bankscope" database actually lists several variables related to banks' off-balance sheets. However a number of problems arose with deriving off-balance sheet data from this source, mostly arising from inconsistency and patchy reporting in the underlying financial statements of banks. A list of issues connected to the "Bankscope" data provided in Appendix 1.

risk-free due to risk of volatile demand for such services as well as reputation risks that may arise from it. Hence the inclusion of such activity in total OBS activity is in our view justified. It is because of the heterogeneity of non-interest income that we prefer the term OBS activity to OBS assets for our work.

The advantage of our approach, like that of Boyd and Gertler, is that it utilizes balance sheet and profit and loss series, which are easier to obtain than OBS asset data and are more consistently reported. The variables used to construct the OBS estimate are net interest income, net non-interest income, provisions on loans and total assets. These are reported in aggregate form for each banking sector in the OECD Banking Income Statement and Balance Sheet online database for our sample period. Table 1 shows the ratios of estimated OBS activity to on-balance sheet activity computed by assuming provisions occur on and off balance sheet in proportion to net income. We report on the corresponding OECD data coverage as well. If the off-balance sheet activity is both risky and less well-regulated than on-balance sheet, then this ratio could play a role in crisis determination models.

An immediate problem with this table is the gaps in the data for Belgium, Canada, France, Italy and Japan (see Appendix 1). A further problem arises with the OECD data, namely the OECD's figures for net non-interest income for Japan and Denmark are negative in some years, indicating higher non-interest expenses incurred compared to non-interest income. The negative ratio of OBS activity to on-balance sheet activity for Norway comes from very large net provisions figure in a corresponding year.

Table 1: Estimated off- to on-balance sheet activity ratios

	Belgium	Canada	Denmark	Finland	France	Germany	Italy	Japan	Neths	Norway	Spain	Sweden	UK	US
1980	na	na	0.66	0.66	na	0.29	na	na	0.46	0.26	0.21	0.54	0.41	0.36
1981	0.18	na	0.74	0.76	na	0.29	na	na	0.55	0.28	0.20	0.53	0.39	0.46
1982	0.24	na	1.05	0.80	na	0.28	na	na	0.47	0.28	0.23	0.57	0.57	0.58
1983	0.29	na	3.13	0.87	na	0.26	na	na	0.41	0.30	0.22	0.57	0.65	0.57
1984	0.22	na	0.25	0.97	na	0.27	0.43	na	0.45	0.40	0.21	0.55	0.71	0.51
1985	0.28	na	2.01	1.19	na	0.32	0.45	na	0.41	0.50	0.23	0.70	0.64	0.54
1986	0.30	na	-0.21	1.18	na	0.31	0.45	na	0.37	0.54	0.22	0.69	0.69	0.64
1987	0.34	na	0.24	1.16	na	0.30	0.39	na	0.36	0.28	0.27	0.49	1.14	0.63
1988	0.44	0.46	0.94	1.57	0.27	0.26	0.38	na	0.39	0.65	0.29	0.56	0.63	0.52
1989	0.42	0.58	0.42	1.09	0.28	0.45	0.34	0.52	0.46	0.66	0.25	0.56	1.22	0.72
1990	0.26	0.49	0.26	0.99	0.34	0.48	0.35	0.52	0.46	0.60	0.26	0.40	0.92	0.62
1991	0.33	0.53	0.30	1.07	0.43	0.38	0.34	0.27	0.50	-1.47	0.28	0.16	1.18	0.63
1992	0.37	0.68	-0.23	1.40	0.76	0.39	0.25	0.16	0.48	0.61	0.32	0.55	1.38	0.55
1993	0.49	0.63	0.46	1.37	1.46	0.40	0.47	0.20	0.59	0.63	0.61	0.88	1.24	0.54
1994	0.40	0.60	-0.19	0.87	1.09	0.32	0.40	0.09	0.44	0.25	0.37	0.51	0.87	0.48
1995	0.51	0.57	0.64	0.27	1.67	0.32	0.33	0.30	0.55	0.34	0.37	0.51	0.86	0.51
1996	0.54	0.60	0.58	0.53	1.45	0.32	0.42	0.12	0.62	0.34	0.45	0.72	0.71	0.56
1997	0.75	0.84	0.54	0.57	1.71	0.39	0.55	1.55	0.73	0.39	0.50	0.89	0.68	0.60
1998	0.79	0.91	0.68	0.36	2.06	0.69	0.68	-0.69	0.78	0.33	0.58	1.35	0.73	0.70
1999	0.68	1.11	0.71	0.53	1.48	0.52	0.71	0.33	0.82	0.36	0.52	1.04	0.77	0.73
2000	1.10	1.32	0.94	0.65	1.94	0.74	0.66	0.08	0.97	0.39	0.67	1.20	0.86	0.76
2001	1.10	1.27	0.81	1.67	2.38	0.79	0.57	-0.82	0.97	0.40	0.52	1.11	0.92	0.83
2002	0.77	1.14	0.71	0.73	1.65	0.90	0.51	-0.67	0.80	0.34	0.58	0.80	0.99	0.81
2003	0.79	0.99	0.80	1.38	1.65	0.60	0.57	0.19	0.75	0.42	0.58	0.85	1.15	0.83
2004	0.57	0.98	0.94	0.67	1.86	0.35	0.53	na	0.77	0.39	0.56	0.82	1.56	0.75
2005	0.64	1.09	0.91	0.51	1.64	0.66	0.55	na	0.89	0.44	0.63	1.07	1.71	0.76
2006	1.39	1.20	1.22	0.60	3.30	0.62	0.76	na	1.09	0.40	0.78	2.24	1.83	0.78
2007	1.69	1.17	1.07	0.75	3.91	0.62	0.61	na	1.32	0.43	0.74	1.36	1.57	0.80

Source: OECD and FSA (for the UK)

Missing observations can be filled in using older versions of the OECD[5] reports or national data where feasible. In limited cases, when no other data are available, gaps are filled by applying the average growth rate of the adjacent three years to the missing year. This is the case in Belgium, Canada, France, Italy and Japan in 1980 and Canada 1980 and 1981.

[5] Bank profitability; Financial statements of banks OECD (hard copy)

As for the negative ratios of OBS to on-balance sheet activities, while the Japanese, Norwegian and Danish banking systems may have faced some stresses around the time of the negative observations, we still need to consider if these negative figures for estimated OBS are realistic. A more appropriate method may be to assume that OBS activity on a gross basis can become zero but cannot be negative. The data after the adjustments and additions are shown in Table 2.

Table 2 illustrates different patterns of OBS activity across countries as well as over time. The majority of countries exhibit higher ratios of off- to on-balance sheet activities over the second half of the period as compared to the first half, although some show much stronger rises in OBS exposures than others. The lowest average ratio over the sample period is observable for Germany, Italy, Japan, Norway and Spain, while France, UK, Finland, Sweden, Canada and Denmark have the highest average ratios. It can be seen that countries' banks often grew their off-balance sheet exposures during tranquil times. For example, UK OBS activity grew strongly in the period up to 2006. The US ratio is around average for these countries, but has also grown over time. Accordingly, we will test whether the change in off-balance sheet exposures and not just the measure for the size of off-balance sheet activity is an important crisis predictor.

Table 2: Estimated off- to on-balance sheet activity ratios with gaps filled and negatives smoothed out

	Belgium	Canada	Denmark	Finland	France	Germany	Italy	Japan	Neths	Norway	Spain	Sweden	UK	US
1980	0.14	0.31	0.66	0.66	0.20	0.29	0.59	0.35	0.46	0.26	0.21	0.54	0.41	0.36
1981	0.18	0.31	0.74	0.76	0.22	0.29	0.52	0.31	0.55	0.28	0.20	0.53	0.39	0.46
1982	0.24	0.34	1.05	0.80	0.23	0.28	0.53	0.24	0.47	0.28	0.23	0.57	0.57	0.58
1983	0.29	0.33	3.13	0.87	0.25	0.26	0.39	0.25	0.41	0.30	0.22	0.57	0.65	0.57
1984	0.22	0.36	0.25	0.97	0.18	0.27	0.43	0.31	0.45	0.40	0.21	0.55	0.71	0.51
1985	0.28	0.38	2.01	1.19	0.21	0.32	0.45	0.37	0.41	0.50	0.23	0.70	0.64	0.54
1986	0.30	0.40	1.07	1.18	0.23	0.31	0.45	0.35	0.37	0.54	0.22	0.69	0.69	0.64
1987	0.34	0.49	0.24	1.16	0.27	0.30	0.39	0.49	0.36	0.28	0.27	0.49	1.14	0.63
1988	0.44	0.46	0.94	1.57	0.27	0.26	0.38	0.62	0.39	0.65	0.29	0.56	0.63	0.52
1989	0.42	0.58	0.42	1.09	0.28	0.45	0.34	0.52	0.46	0.66	0.25	0.56	1.22	0.72
1990	0.26	0.49	0.26	0.99	0.34	0.48	0.35	0.52	0.46	0.60	0.26	0.40	0.92	0.62
1991	0.33	0.53	0.30	1.07	0.43	0.38	0.34	0.27	0.50	0.64	0.28	0.16	1.18	0.63
1992	0.37	0.68	0.42	1.40	0.76	0.39	0.25	0.16	0.48	0.61	0.32	0.55	1.38	0.55
1993	0.49	0.63	0.46	1.37	1.46	0.40	0.47	0.20	0.59	0.63	0.61	0.88	1.24	0.54
1994	0.40	0.60	0.60	0.87	1.09	0.32	0.40	0.09	0.44	0.25	0.37	0.51	0.87	0.48
1995	0.51	0.57	0.64	0.27	1.67	0.32	0.33	0.30	0.55	0.34	0.37	0.51	0.86	0.51
1996	0.54	0.60	0.58	0.53	1.45	0.32	0.42	0.12	0.62	0.34	0.45	0.72	0.71	0.56
1997	0.75	0.84	0.54	0.57	1.71	0.39	0.55	1.55	0.73	0.39	0.50	0.89	0.68	0.60
1998	0.79	0.91	0.68	0.36	2.06	0.69	0.68	1.02	0.78	0.33	0.58	1.35	0.73	0.70
1999	0.68	1.11	0.71	0.53	1.48	0.52	0.71	0.33	0.82	0.36	0.52	1.04	0.77	0.73
2000	1.10	1.32	0.94	0.65	1.94	0.74	0.66	0.08	0.97	0.39	0.67	1.20	0.86	0.76
2001	1.10	1.27	0.81	1.67	2.38	0.79	0.57	0.12	0.97	0.40	0.52	1.11	0.92	0.83
2002	0.77	1.14	0.71	0.73	1.65	0.90	0.51	0.15	0.80	0.34	0.58	0.80	0.99	0.81
2003	0.79	0.99	0.80	1.38	1.65	0.60	0.57	0.19	0.75	0.42	0.58	0.85	1.15	0.83
2004	0.57	0.98	0.94	0.67	1.86	0.35	0.53	0.08	0.77	0.39	0.56	0.82	1.56	0.75
2005	0.64	1.09	0.91	0.51	1.64	0.66	0.55	0.15	0.89	0.44	0.63	1.07	1.71	0.76
2006	1.39	1.20	1.22	0.60	3.30	0.62	0.76	0.10	1.09	0.40	0.78	2.24	1.83	0.78
2007	1.69	1.17	1.07	0.75	3.91	0.62	0.61	0.03	1.32	0.43	0.74	1.36	1.57	0.80
Average	0.57	0.72	0.83	0.90	1.18	0.45	0.49	0.33	0.64	0.42	0.42	0.79	0.96	0.64

In order to provide a better understanding of factors underlying these developments, we provide charts for the determinants of the ratio, namely net interest income, net non-interest income and provisions on loans over the entire sample period (allowing for missing observations) in Appendix 5. As would be expected, countries with the lowest average ratios of OBS activity in general saw non-interest income falling short of net interest income. However for countries having the highest ratios of OBS exposures, we observe non-interest income growing faster than net interest income, specifically over 2001-2007, and in several cases outstripping it. For example, in the UK over 2002-2007, non-interest income on average grew by 14.7% per annum compared with 10% in 1996-2001, while net interest income growth fell from 9% per annum in 1996-2001 to 6.2% in 2002-2007.

4 Estimation and results

As already noted above, the baseline for our analysis is the approach to crisis determination set out in Barrell et al (2010). They used a panel multinomial logit approach with banking crises as the dependent variable (see Appendix 7). As independent variables, they looked at the role of unadjusted capital adequacy (LEV), bank's narrow liquidity ratios (NLIQ), real house price growth (RHPG) and the current balance as a percent of GDP (CBR) along with the more traditionally used variables, GDP growth (YG), domestic credit growth (DCG), the M2/FX reserves ratio (M2RES), inflation (INFL), real interest rates (RIR) and budget balance to GDP ratio (BB) (see for example, Demirguc-Kunt and Detragiache, 1998, 2005). Barrell et al found, however, that the traditional variables are not relevant for crisis determination in OECD countries. Rather, the probability of banking crisis in 14 OECD countries can be predicted by four "new" variables: two macroprudential indicators, banks' unadjusted capital adequacy and narrow liquidity and two real economy "vulnerability" variables, the change in real residential property prices and the current account to GDP ratio. These had not been used in previous work on banking crisis prediction because the bank variables and house prices are typically not available for developing or emerging market countries.

These four crisis-prediction variables are in our view highly plausible and consistent as causes of banking crises. The first two show how robust the banking system is to shocks, in terms of capital and liquidity buffers. Meanwhile, the macroeconomic variables distinguish unbalanced booms which are characterised by rapid growth in consumption and housing investment, implying that supply fails to keep pace with respective demand. In such a context, the quality of lending is likely to deteriorate, given lending assets the banks take on in such booms will sharply deteriorate in the ensuing downturn. It is plausible that credit and GDP are unable to distinguish crises as well as these variables since credit and output may also expand in a situation of balanced growth where supply and demand balance is maintained both economy-wide and in the property sector.

Although this model was shown to be extremely robust, a more comprehensive model would encompass the risks generated by banks' off-balance sheet positions. As previously noted, capital adequacy and liquidity ratios may appear healthy in terms of on-balance sheet activity but do not necessarily compensate for risky off-balance sheet activities. Therefore we add variables that are intended to capture banks' OBS activities as shown above, and use the general to specific approach to arrive at the final specification of the equation. We check for in-sample performance of the model and conduct a set of robustness tests to assess the sensitivity of our results. We look at crises in 14 OECD countries over the period 1980 to 2008, with the choice of countries dictated by data availability in the OECD source.

We again use a multinomial logit method to regress a banking crisis variable (which is one for the onset of the crisis and 0 otherwise) on the four variables cited in Barrell et al (2010) together with all the "traditional" crisis determinants mentioned in the literature[6] and measures of banks' OBS activity. Both the level of the ratio (defined as OFF TO ON) and the change in the ratio (defined as D(OFF TO ON)) of off to on-balance sheet activities are used as a proxy for off-balance sheet related risks. We employ the difference as well as the level since the ratio on its own may not be enough to capture the trends developing in the banks' OBS activities. Some countries with historically high off- to on-balance sheet ratios do not necessarily have higher exposure to risk. On the other hand, those experiencing significant

[6] Different results on the cuases or at least predictors of crises will imply different policy recommendations. For example the negative result in Barrell et al (2010) for credit growth, and its lack of predictive power in Granger causality tests between house price growth and credit growth casts doubt on the usefulness of reserving cyclically against credit growth, as in Spain.

increases can be undergoing shifts in business strategies which expose them to new, untested risks, with possible adverse selection, for example. This is consistent with what Davis (1995) calls the "industrial organization" approach to financial instability, which suggests new entry and structural change in financial markets is a key determinant of risk taking and hence of crises.

Once all variables are added, we eliminate insignificant variables step-by-step, starting with the most insignificant ones first. Table 3 shows the results of the testing down process, starting from the general form and finishing with the final form of our model[7]. It can be seen, that throughout all stages of the elimination process, the first five variables in the table (namely leverage and liquidity ratios, changes in house prices, the current account balance/GDP ratio and the difference of the off to on-balance sheet activities ratio) remained highly significant with slight variation in their parameters. The opposite is true for all the remaining variables, including the level of the OFF TO ON ratio, all of which were highly insignificant (except for DCG which was significant at the 90% level almost until the last step).

Table 3: Estimation results

LEV(-1)	-0.392 (2.574)	-0.39 (2.593)	-0.373 (2.648)	-0.331 (2.923)	-0.359 (3.467)	-0.35 (3.463)	-0.321 (3.388)	**-0.371** **(4.121)**
NLIQ(-1)	-0.156 (2.967)	-0.157 (3.047)	-0.152 (3.087)	-0.154 (3.127)	-0.152 (3.107)	-0.139 (3.282)	-0.127 (3.261)	**-0.123** **(3.249)**
RHPG(-3)	0.099 (2.475)	0.099 (2.488)	0.1 (2.554)	0.104 (2.681)	0.101 (2.603)	0.091 (2.664)	0.089 (2.635)	**0.079** **(2.345)**
CBR(-2)	-0.266 (2.604)	-0.265 (2.615)	-0.27 (2.706)	-0.259 (2.677)	-0.273 (2.902)	-0.28 (3.052)	-0.253 (2.947)	**-0.256** **(3.04)**
D(OFF TO ON(-2))	0.023 (2.472)	0.023 (2.481)	0.023 (2.475)	0.026 (3.519)	0.026 (3.543)	0.025 (3.556)	0.024 (3.562)	**0.022** **(3.433)**
DCG(-1)	-0.097 (1.771)	-0.096 (1.772)	-0.096 (1.769)	-0.095 (1.744)	-0.096 (1.752)	-0.094 (1.755)	-0.065 (1.414)	-
YG(-1)	0.192 (1.243)	0.193 (1.25)	0.193 (1.248)	0.191 (1.235)	0.182 (1.167)	0.157 (1.062)	-	-
BB(-1)	-0.048 (0.541)	-0.049 (0.551)	-0.054 (0.612)	-0.059 (0.681)	-0.046 (0.548)	-	-	-
M2RES(-1)	-3E-5 (0.524)	-3E-5 (0.526)	-3E-5 (0.567)	-3E-5 (0.549)	-	-	-	-
OFF TO ON(-2)	0.003 (0.513)	0.003 (0.515)	0.003 (0.521)	-	-	-	-	-
RIR(-1)	0.031 (0.306)	0.021 (0.341)	-	-	-	-	-	-
INFL(-1)	-0.02 (0.126)	-	-	-	-	-	-	-

Note: sample period 1980-2008; and hence estimation period 1983 to 2007;z-stat in parenthesis; Unweighted capital adequacy ratio (LEV), narrow liquidity/assets ratio (NLIQ), change in real house prices (RHPG), current account/GDP ratio (CBR), change in off/on-balance sheet activities ratio (D(OFF TO ON)), real domestic credit growth (DCG), real GDP Growth (YG), fiscal surplus/GDP ratio (BB), M2/ Foreign Exchange Reserves ratio (M2RES), off/on-balance sheet activities ratio(OFF TO ON), inflation (INFL), real interest rate (RIR).

[7] We experimented with the lag length of OFF TO ON and D(OFF TO ON) variables, by adding up to four lags of each variable separately and eliminating ones that were insignificant and/or have a wrong sign. The second lag for both the level and difference variables was found to be significant, generating the positive coefficient.

These results are in line with the findings of Barrell et al (2010), showing that in OECD countries, asset price booms with an accompanying current account imbalance and lower defences from less stringent bank regulation, are the most important factors driving the probability of a banking crisis. And although lax monetary policy and credit booms may at times contribute to banking crises, they are not the most powerful discriminators between times of crisis onset and other periods in OECD countries.

As can be seen from Table 3, the change in the off/on-balance sheet activities ratio is significant in addition to capital adequacy (LEV), the liquid asset ratio (NLIQ), the growth rate of real house prices (RHPG) and the current account to GDP ratio (CBR). The variable proxying changes in banks' OBS activities has a positive effect on the probability of a crisis[8], hence, expansion of OBS activities relative to on-balance sheet assets by the banks increases crisis probability.

We check for the in-sample performance of the final model and as shown in Table 4, the false call rate when there is no crisis, known as the Type II error, is 26.5% and the false call rate when there is a crisis, known as the Type I error is 20%, i.e. we only miss one in five crises. The overall successful call rate (both crisis and no crisis called correctly) is 74%, with 16 out of the 20 crisis episodes captured correctly at a cut-off point of 0.055[9]. Adding D(OFF TO ON) improves the fit of the equation as compared to the version by Barrell et al (2010), as we are able to capture correctly both more crises as well as non crisis periods (Appendix 3 lists the estimation results together with the in-sample performance of the earlier model for comparison).

Table 4: In-sample model performance

	Dep=0	Dep=1	Total
P(Dep=1)<=0.055	253	4	257
P(Dep=1)>0.055	91	16	107
Total	344	20	364
Correct	253	16	269
% Correct	73.6	80.0	73.9
% Incorrect	26.5	20.0	26.1

Looking in more detail at the in-sample performance of the model (charts illustrating in-sample probabilities for every country are presented in Appendix 6), all the systemic banking crises are identified (see the crisis list in Appendix 7). Moreover, in the case of the four missed crises (Italy 1990, UK 1995, Germany and Netherlands 2008) none can be considered systemic. As for the so-called false alarms (Type II errors), more than half of them occur prior to and/or after the crises onset, indicating that our model, on the top of identifying crisis, is able to differentiate between periods of financial stability and instability very well.

Table 5 analyses in-sample performance country by country. The first column shows the total number of calls recorded by the model above the threshold value of 0.055. The next two columns depict the number of crises called when there is a crisis, and the number of crises

[8]Table A1 in Appendix 3 show that these variables are not strongly correlated, suggesting that the change in OBS is orthogonal to the other regressors in the equations, and hence multicollinearity and omitted variable bias in our equations that omit this variable are not an issue. This is reinforced by the stable nature of parameters as variables are dropped from the equation.

[9] Calculated as the sample mean for onset of crises i.e. 20/364. We could of course use some other cut of point for the crisis call, and this should depend on the weightings in the loss function for a false call when there is no crisis to the loss from failing to call an actual crisis. If we wished to set a cut off to call all crises then we would have around 282 false calls when there is no crisis.

recorded when there is no crisis. The fourth column shows the number of crises recorded by the model continuously in the run up to a crisis or its aftermath (where the varying "window" and the crisis year itself are shown in the final column). In these cases the model was either predicting the crisis or indicating its after-effects. The fifth column is the difference between the third and fourth columns, i.e. "false calls after correction".

Accordingly, to calculate an "adjusted" number of false calls, we first identify false calls occurring in the periods adjacent to the onset of crisis (column 4) and then subtract them from the initial number of false calls (result in column 5). This leaves us with 49 instead of 91 initial false calls. The effect of timing is most apparent in the UK, which incidentally has the largest number of crises recorded over our sample period. The UK appears to have the largest number of false calls, but once the timing is taken into account, only 1 "true" false call remains. Therefore, the build up of vulnerabilities in the economy prior to the crisis combined with the weakened banking system and current account after the crisis is the reason for a comparatively high number of false calls that our model has produced. Similar patterns are observed in France, Japan and Finland, which have the largest number of false calls after the UK. Here as well, once the timing of the crisis is accounted for, the adjusted type II proportion drops by around 60% in France and by 40-55% in Japan and Finland.

Table 5: Breakdown of in-sample predictions

	Total calls	Crisis called	False calls (as produced by model)	False calls prior/after crisis	False calls after correction for timing	Timing of false calls
Belgium	1	1	0	0	0	
Canada	9	1	8	1	7	next year (1983)
Denmark	6	1	5	0	5	
Finland	10	1	9	4	5	prior 1 year and following 3 years(1991)
France	18	2	16	7	7	prior 6 years and next year (1994)
				2		prior 2 years (2008)
Germany	1	0	1	0	1	
Italy	0	0	0	0	0	
Japan	11	1	10	4	6	prior 2 years and next 2 years (1991)
Netherlands	5	0	5	0	5	
Norway	3	1	2	2	0	prior 2 years(1990)
Sweden	8	1	7	3	4	next 3 years(1991)
Spain	4	0	4	0	4	
UK	21	4	17	4	1	prior 1 year and following 3 years (1984)
				5		prior 3 years and following 2 years (1991)
				7		prior 7 years (2007)
US	10	3	7	3	4	next 3 years(1988)
Total	107	16	91	42	49	

As a next step, we split a sample into three sub-periods; up to 1989, 1990-1999 and 2000-2008, and investigate whether any of the above sub-periods are characterized by higher or lower number of false calls. We found that the number of false calls in each sub-period is quite even on the aggregate level. On the other hand, the country-by-country breakdown shows different levels of concentrations of false calls. Focusing only on the calls that are not adjacent to the occurrence of a crisis ("adjusted" calls) as defined above, we observe that Canada has 6 out of 7 false calls recorded before 1993, (the period prior to the introduction of inflation targeting by the Bank of Canada); Finland has most of its false calls occurring in the early 80's (between 1983 and 1987), a period when we observe significant rises in house prices following financial liberalisation; and for Spain, although there was no official record of systemic or non-systemic crises in 2007 or 2008, our model shows a substantial increase in vulnerabilities in the run up to and over the subprime crisis and this is verified by banking difficulties in that country which are now coming to light (see for example Financial Times (2010)). Therefore, it appears that the vast majority of false calls reported by the model are associated with periods of risk accumulation in the economies or with periods of weakened economic conditions in the aftermath of crises.

We ran a set of robustness tests, first by changing the time period of estimation, then by dropping one-by-one countries with the largest number of crises and finally using the *d(off to on)* variable without missing observations filled in (effectively estimating an unbalanced panel). First, the time period was shortened to 1980-2006, to eliminate the possibility that the positive results are driven solely by the impact of crises in the sub-prime crisis period (2007-2008) on the estimation results, since these are when most comment on OBS effects on crises have arisen. Also the sub-prime episodes constitute 40% of all crisis observations in our sample. Second and third, the UK and the US have the highest number of crises recorded over the period of our analysis (5 and 3 correspondingly), so we exclude them from the estimation one at a time to investigate whether either of them have a significant impact of the final results. And finally, we recalculate the *d(off to on)* variable so it omits missing observations in Canada, France Italy and Japan (gaps are illustrated in Table 1). Our aim in running this unbalanced panel is to check whether adding spliced data could have had a significant effect on the estimated coefficients.

These tests are reported in Table 6 and in no case is there a significant or noticeable change in the coefficients of our driving variables or their significance levels, indicating that we have a robust specification of the model.

Table 6: Robustness test results

	Full sample	Excluding subprime crisis period	Excluding UK	Excluding US	Allowing for missing observations for OBS
LEV(-1)	-0.371	-0.569	-0.41	-0.454	-0.397
	(-4.121)	(-4.645)	(-3.955)	(-4.28)	(-4.122)
NLIQ(-1)	-0.123	-0.097	-0.127	-0.108	-0.106
	(-3.249)	(-2.359)	(-3.126)	(-2.805)	(-2.584)
RHPG(-3)	0.079	0.09	0.115	0.095	0.079
	(2.345)	(2.226)	(2.943)	(2.495)	(2.283)
CBR(-2)	-0.256	-0.464	-0.243	-0.2	-0.262
	(-3.04)	(-3.074)	(-2.847)	(-2.338)	(-2.973)
D(OFF TO ON(-2))	0.022	0.023	0.023	0.024	0.022
	(3.433)	(2.884)	(3.319)	(3.534)	(3.416)

Note: z-stat are in parenthesis

Having specified the model and checked its robustness, we decompose probabilities of crisis according to their drivers. First we look at the contribution of OBS activity alone to the changes in crisis probabilities in all countries over the entire estimation period and we then present decomposition results for the countries where our model picked the crises occurrences correctly in 2008 (the UK, the US, Belgium, France) plus Spain, where, as noted above, significant banking problems also appear to be present[10].

Decomposition analysis is undertaken based on the final equation for calculating probabilities (*pcrisis*) in each country (denoted by i):

[10] Due to the lag structure of the variables we will be looking at the movements in the variables seven years prior to financial crisis.

$$pcrisis_{i,t} = \frac{1}{1+e^{-\left(-0.37lev_{i,t-1} - 0.12nliq_{i,t-1} + 0.08rphg_{,t-3} - 0.26cbr_{i,t-2} + 0.02dofftoon_{i,t-2}\right)}} \qquad (3)$$

The contribution of each variable to the change in the probability between the adjacent years is calculated by subtracting the probability generated based on the final lag structure of all variables apart from one (which is taken with extra lag) from the probability with lag structure of variables based on the final specification. These are described in the literature as the time specific marginal effects of each of the variables. The example below, where subscripts *i,l,t* denote country, variable (which is taken with extra lag) and time period correspondingly, illustrates how the contribution of unadjusted capital adequacy (LEV) is calculated:

$$pcrisis_{i,t} - pcrisis_{i,l,t-1} =$$

$$\frac{1}{1+e^{-\left(-0.37\,lev_{i,t-1} - 0.12\,nliq_{i,t-1} + 0.08\,rphg_{i,t-3} - 0.26\,cbr_{i,t-2} + 0.02\,dofftoon_{i,t-2}\right)}} - \frac{1}{1+e^{-\left(-0.37\,lev_{i,t-2} - 0.12\,nliq_{i,t-1} + 0.08\,rphg_{i,t-3} - 0.24\,cbr_{i,t-2} + 0.02\,dofftoon_{i,t-2}\right)}} \qquad (4)$$

Table 7 shows the part OBS exposures played in the changes of crisis probabilities for a given year. Years when banking crises took place are in bold. Out of 20 crises in the sample, 11 were accompanied by a positive contribution by OBS. 3 out of the remaining 9 was missed by the model (already discussed above), and the remaining 6 crises were caused by other factors. Among the systemic banking crises (Appendix 7), only those in the US and Norway showed an increased contribution from the OBS component.

Table 7: Contribution of OBS activity to the changes in crisis probabilities

	BG	CN	DK	FN	FR	GE	IT	JP	NL	NW	SD	SP	UK	US
1984	0.001	0.002	0.001	-0.013	0.000	0.000	0.007	-0.005	-0.003	0.000	0.001	0.000	**0.031**	0.000
1985	0.000	-0.002	0.155	0.005	0.000	0.000	-0.001	0.010	0.000	0.000	0.000	0.000	-0.017	-0.006
1986	-0.003	0.003	-0.513	0.007	-0.012	0.001	0.001	0.008	0.002	0.001	0.000	0.000	-0.003	-0.003
1987	0.003	-0.001	**0.516**	0.024	0.010	0.001	0.000	0.000	-0.002	0.000	0.005	0.000	-0.028	0.008
1988	-0.001	0.001	-0.727	-0.025	-0.001	-0.001	0.000	-0.008	0.000	-0.018	-0.003	0.000	0.025	**0.010**
1989	0.001	0.015	0.001	-0.001	0.005	0.000	0.000	0.020	0.002	-0.087	-0.004	0.000	0.169	-0.022
1990	0.003	-0.038	0.017	0.124	-0.011	0.000	**0.000**	-0.003	0.002	**0.281**	0.014	-0.001	-0.412	-0.015
1991	-0.006	0.047	-0.061	**-0.446**	0.002	0.005	0.000	**-0.037**	0.002	-0.035	**-0.013**	-0.001	**0.542**	0.040
1992	-0.005	-0.047	0.002	0.143	0.014	-0.005	0.002	0.018	-0.006	-0.004	-0.046	0.001	-0.428	-0.023
1993	0.002	0.013	0.002	0.032	0.007	-0.009	0.000	-0.045	0.003	0.002	-0.010	0.000	0.042	0.003
1994	0.000	0.006	0.003	0.035	**0.051**	0.005	-0.001	0.009	-0.004	-0.001	0.061	0.000	-0.007	-0.002
1995	0.001	-0.021	0.000	-0.012	0.064	0.000	0.001	0.007	0.006	0.000	-0.004	0.001	**-0.022**	0.002
1996	-0.002	0.002	0.001	-0.003	-0.117	-0.004	-0.001	-0.009	-0.010	-0.003	-0.009	-0.002	-0.008	-0.002
1997	0.002	0.000	-0.004	-0.001	0.081	0.004	0.000	0.036	0.010	0.004	0.016	0.001	0.029	0.004
1998	-0.001	0.003	-0.003	0.007	-0.064	0.000	0.000	-0.060	-0.002	-0.003	0.011	0.001	-0.010	0.001
1999	0.002	0.026	0.002	-0.005	0.020	0.003	0.000	0.364	0.002	0.001	-0.002	0.000	0.012	0.000
2000	-0.001	-0.023	0.018	-0.006	0.004	0.016	0.000	-0.169	-0.008	-0.008	0.041	0.000	0.013	0.005
2001	-0.001	0.011	-0.014	0.008	-0.027	-0.038	-0.002	-0.001	-0.001	0.004	-0.104	-0.005	-0.004	-0.009
2002	0.012	0.001	0.028	0.000	0.082	0.035	-0.002	0.002	0.035	0.000	0.038	0.013	0.016	-0.001
2003	-0.007	-0.015	-0.030	0.005	-0.001	-0.012	-0.002	0.003	-0.044	0.000	-0.035	-0.018	-0.010	0.006
2004	-0.003	-0.004	0.003	-0.005	-0.066	0.002	0.001	0.000	-0.026	-0.002	-0.008	0.013	0.003	-0.015
2005	0.008	-0.001	0.016	0.021	0.036	-0.014	0.007	0.000	0.008	0.002	0.006	-0.009	0.035	0.003
2006	-0.010	0.009	0.006	-0.016	0.044	0.001	-0.005	0.000	0.004	-0.001	-0.002	-0.007	0.127	-0.009
2007	0.023	0.010	-0.016	0.004	-0.126	0.012	0.004	0.000	0.008	0.000	0.014	0.045	**-0.135**	**0.010**
2008	**0.197**	0.000	0.108	0.006	**0.775**	**-0.009**	0.006	0.000	**0.003**	0.000	0.138	0.050	**-0.007**	**0.004**

Similar calculations were undertaken for the other four remaining variables. As the relationship is not linear, the sum of all contributions from the right hand side variables are not exactly equal to the change in the dependent variable. The remaining term accounts for the interaction between the independent variables, which can be computed by summing two or three individual marginal contributions and comparing that to a marginal contribution where two or three of the driving variables are allowed to vary. We call the sum of these terms the adjustment (Adj) for interaction and add it to the direct contributions of the right hand side variables. The cumulative change in the probability and its contributing variables over a certain time period is just a sum of the changes in the probabilities and the sum of contributions by each variable over the same time span.

For the sake of brevity we do this only for France, Belgium, Spain, the US and the UK in the five years prior to the subprime crisis. The detailed decomposition analysis is presented in Table 8. The first column of the table shows the crisis probability level for the country in each year, whilst the next six columns illustrate the role year-on-year changes in the independent variables played in changes in probability described in the equation above. The final column is the total change in the initial level from year to year that the contributions sum to. The bottom row shows the cumulative change in probability over the whole period (i.e. from 2004 to 2008). In all cases, OBS proxy variable have contributed positively to the increase in the probabilities of crises, although the size of the impact differs. For France and Belgium, sizeable increases in the crisis probabilities were driven by the change in OBS activity, with the largest effect coming from the change between 2007 and 2008. In other countries, other variables were the main contributors to the rise in probabilities, although a role is found for OBS exposures in all of them.

Table 8: Contribution to changes in crisis probabilities for selected countries

Belgium		Contribution to change in probability						
	Probability	NLIQ	LEV	RHPG	CBR	DOFFTOON	Adj for Interaction	Change in probability
2004	0.003	na	na	na	na	na	na	na
2005	0.015	0.004	0.002	0.003	0.002	0.008	0.007	0.012
2006	0.015	0.004	0.002	-0.001	0.002	-0.010	-0.004	0.000
2007	0.051	0.010	-0.005	0.012	0.010	0.023	0.014	0.036
2008	0.272	0.058	-0.089	0.064	0.031	0.197	0.040	0.221
Sum of changes	na	0.076	-0.090	0.077	0.045	0.218	0.057	0.269

France		Contribution to change in probability						
	Probability	NLIQ	LEV	RHPG	CBR	DOFFTOON	Adj for Interaction	Change in probability
2004	0.006	na	na	na	na	na	na	na
2005	0.046	0.007	0.005	0.004	0.006	0.036	0.017	0.040
2006	0.131	0.011	0.030	0.023	0.006	0.044	0.030	0.085
2007	0.106	0.016	-0.008	0.024	0.027	-0.126	-0.043	-0.025
2008	0.895	-0.000	0.013	0.001	0.001	0.775	-0.000	0.789
Sum of changes	na	0.034	0.040	0.051	0.039	0.729	0.004	0.889

Spain		Contribution to change in probability						
	Probability	NLIQ	LEV	RHPG	CBR	DOFFTOON	Adj for Interaction	Change in probability
2004	0.035	na	na	na	na	na	na	na
2005	0.067	0.022	-0.012	0.026	0.004	-0.009	-0.001	0.032
2006	0.173	0.031	0.040	0.017	0.055	-0.007	0.030	0.106
2007	0.398	0.065	0.044	-0.013	0.120	0.045	0.037	0.225
2008	0.479	-0.021	0.016	-0.063	0.098	0.050	-0.001	0.081
Sum of changes	na	0.097	0.089	-0.033	0.277	0.079	0.064	0.444

UK		Contribution to change in probability						
	Probability	NLIQ	LEV	RHPG	CBR	DOFFTOON	Adj for Interaction	Change in probability
2004	0.116	na	na	na	na	na	na	na
2005	0.241	0.002	0.010	0.099	-0.007	0.035	0.015	0.125
2006	0.442	0.009	0.057	-0.008	0.031	0.127	0.016	0.201
2007	0.292	-0.002	0.024	-0.066	0.026	-0.135	-0.003	-0.151
2008	0.253	0.010	0.026	-0.119	0.036	-0.007	-0.015	-0.038
Sum of changes	na	0.020	0.118	-0.094	0.087	0.020	0.013	0.137

US		Contribution to change in probability						
	Probability	NLIQ	LEV	RHPG	CBR	DOFFTOON	Adj for Interaction	Change in probability
2004	0.074	na	na	na	na	na	na	na
2005	0.045	-0.017	-0.015	-0.002	0.004	0.003	0.001	-0.029
2006	0.043	0.002	-0.000	-0.002	0.006	-0.009	-0.001	-0.002
2007	0.064	0.002	-0.008	0.011	0.008	0.010	0.002	0.021
2008	0.087	0.004	0.004	0.010	0.002	0.004	0.002	0.023
Sum of changes	na	-0.008	-0.019	0.017	0.019	0.008	0.004	0.013

5 Policy Implications

In assessing OBS activity and the appropriate regulatory response, it should first be acknowledged that off-balance sheet activity can be productive, it can spread risks and fill holes in the market, in effect bringing the economy closer to Arrow-Debreu optimum by creating a wider range of contingent markets. These should increase welfare and increase output. However, it was clear in the recent crisis that structures became too complex and risks too opaque, and regulators found it difficult to set up defences against the systemic risks involved. Accordingly, policy action is required.

The results have direct implications for macroprudential policy, since they suggest that changes in the OBS ratio have a major impact on the likelihood of a systemic crisis. In order to offset this, the authorities can either directly target the required ratios of off- to on-balance sheet activities, implying direct limits on banks' activities at micro level[11], or increase capital and/or liquidity requirements for banks at macro level, thus counteracting and dampening amplified risk exposure from elevated levels of OBS activity. Both of these approaches would require significantly better monitoring of OBS, and regulatory changes would be necessary to ensure this, which we discuss in the following paragraphs.

It is important that there is international agreement on regulation of OBS to prevent 'competition in laxity' and ensure a level playing field. The Bank for International Standards (BIS) and the Basel Agreements are meant to achieve this. However, this requires the cooperation of all major parties and a commitment to common goals. In this context, an

[11] To give an idea of the magnitudes concerned, we present in Appendix 8 calculations of required changes in the OBS proxy to ensure crisis probabilities in each country and in each year in our sample do not exceed the sample average.

interesting sideline to our research is the difficulty of detecting banking crises in 2007-8 in Germany and the Netherlands with our model. One aspect of the difficulties in those countries is that the banks purchased large quantities of securitized US assets, some of which were held on balance sheet and some in SIVs and conduits. There were no other indications of financial risk in those countries such as house price booms, balance of payments deficits or capital or liquidity shortages as measured, and that is why the model fails to detect the risk. This underlines the need for accurate measurement of OBS at a global as well as a national level and also for international cooperation of (in this case) the US authorities in communicating their assessment of risks on these instruments to cross border banks which are exposed to the related risks.

There are a number of options that have to be considered as further regulatory responses to the problems we have seen related to OBS activity, which is of course highly diverse. One would involve changes to the (mainly US) model of separating the origination and the distribution of assets. If the originator of a loan has no stake in its risks once it is sold on, then there is less incentive to properly evaluate the risk. There may be a need to ensure that a significant proportion of the securities are retained by the originator ("skin in the game"). Or alternatively, residual obligations could be written into change of ownership contracts, and this could be enforced.

Other proposals to reduce the scale of OBS activity involve taxes on credit and taxes on transactions. These are two different issues, and they are designed to address two different problems. Taxes on credit would reduce level of borrowing by individuals, but not necessarily affect the cyclicity of asset prices, and that would be essential. Hence although there is no reason why taxes on credit should not be used to raise revenue it is not clear that they will reduce the risks of crises. The same might be said of transactions taxes and bank taxes designed to contribute to a fund to cover future costs. Indeed, there is evidence that such schemes increase the risk of crises, as they are similar to deposit insurance, and its impact on crisis probabilities is clear in the literature. Perhaps the only sound reason for taxing transactions (apart from revenue) is to make sure that there is a proper record, and this could be achieved by requiring recourse loans were all registered (if you do not register, you cannot enforce the loan).

Clearing houses and registers serve the same purpose, as recording and understanding contracts is also essential to regulating markets. OBS have been underestimated in part because there was no register of such activities, and especially a chronic dearth of information on over-the-counter (OTC) trades. Creating central counterparties, or clearing houses for off-balance sheet activities and in particular for OTCs would be a very effective way of ensuring regulators could respond, and to the extent it involves transactions costs it would reduce the scale of such activities (IMF 2009).

In this context, as a specific macroprudential instrument, Barrell and Weale (2010) suggest stamp duties on all OBS trades as a way of recording them, and Singh (2010) has suggested there could be a tax based on over-the-counter payables in derivative markets. It would be based on off-balance-sheet data, including netted exposures, thus measuring the potential systemic interconnectedness of these contracts more accurately. On the other hand as pointed out by IMF (2010), the tax would only be based on banks' OTC derivative payables. It does not increase institutions' capital base, nor would it take into account second-round contagion effects.

On balance, overall, financial regulations are changing in response to the crisis, and the core problems behind the current crisis seem likely to be addressed, with the scale and complexity of OBS financial products almost certainly being restricted. Of course other problems may emerge and financial innovations may get round new regulations, as Goodhart (2008) discusses. Hence the need for continuous monitoring and adaptation of regulation of banks and financial markets.

6 Conclusions

We have estimated the off-balance sheet exposures of the banking systems by employing the ratio of off- to on-balance sheet activities in an econometric model of crisis determination. We checked for the significance of both the ratio and the change in the ratio of off- to on-balance sheet activities and found that along with capital, liquidity, property price growth and current account deficits, changes in the off- to on-balance sheet activities ratio has a positive and significant effect on the probability of a banking crisis. The inclusion of such a proxy variable for banks' OBS activity in the estimation improved in-sample performance of the model, with more crisis periods being captured and the number of false calls reduced. 80% of crises were captured and once the timing of the false calls was accounted for, the number of false calls dropped from 26.5% to 14%. We ran several robustness tests and we conclude that the model is well specified.

Decomposition analysis looking at the driving factors behind the change in probabilities from year to year reveals that, out of 20 crises in the sample 11 were accompanied by increases in OBS activity. At the same time, in all countries where our model has flagged the crisis correctly in 2008, the OBS proxy variables have contributed positively to the increase in the probabilities of banking crises.

Regulation needs to respond to the risks posed by OBS activities, with controls needed at a macroprudential as well as a microprudential level. Reducing the scale and complexity of OBS activity may be essential, and there are several ways to do this. Registers and clearing houses may make OBS activity more transparent and easier to provision against. And requiring mandatory holdings or recourse on securitized assets may also be beneficial. Taxes on OTC derivatives might also be considered.

Overall our findings can be considered as a step towards quantifying the effect OBS activity has on the occurrence of a crisis. Further investigation in this area can be conducted once more detailed data are available, which will allow researchers to adjust banks liquidity and leverage ratios for the size of the OBS exposures directly and test for impact on crisis probabilities more precisely. Given how essential such calculations are, we would suggest direct regulatory action (to produce that data) would be wise.

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APPENDIX 1

Data Issues in Using Bankscope

In order to obtain country-level measures, the user has to aggregate the OBS series for individual banks within a country. This requires a judgment on the shareholder criteria used for the aggregation: for example, we opted to include all banks in an economy where at least 50% of the shares were owned domestically. This excluded banks with majority foreign ownership but which may have held significant amounts of OBS exposures within the domestic system.

The aggregated data for each country showed major time series problems:

1. Bankscope only allowed us to access data back to 2001 which meant the OBS series were shorter than the remaining sample period (1980 – 2007). This meant we had to make the crude assumption that OBS activity prior to 2001 had remained stable in each country in order to fill the missing observations.[12]
2. Even when Bankscope covered the years, many individual observations of OBS within each series were missing. Due to points (3) and (4) below, it was impossible to replace such missing observations with reliable alternative data points.
3. Bankscope's OBS assets series prior to 2004 are particularly patchy in their coverage with countries such as Finland having far fewer observations than others (such as Germany, Denmark and the USA).
4. We construct the off-balance sheet exposures for a banking system by aggregating the figures for all banks that comprise the top 80% of total banking system assets. The problem with Bankscope data is that the banks that comprise the top 80% with OBS data vary vastly from year to year. For example, in France in 2004, Credit Agricole SA was the largest bank in terms of assets, yet this bank does not contribute to the top 80% of assets in 2002; the bank only starts reporting in 2004. Thereon, Credit Agricole forms a large part of the French off-balance sheet exposures. Such anomalies make the Bankscope data extremely volatile at best and unreliable at worst.

Data Issues in Using the: OECD Bank Income and Balance Sheet Dataset

1. The UK does not report data to the OECD prior to 1984, although from there on, figures are available till 2007. Because the FSA were able to provide us with consistent series for the entire sample period, we opted to use their data for the UK. The FSA data covered all large UK commercial banks and were compatible with the OECD figures we could access.
2. The OECD data for Japan are missing from 2004 onwards. It is possible to substitute the missing observations with data from the Japanese Banker's Association but there remain difficulties with obtaining consistent estimates of non-interest income from the two sources.
3. Belgium, Canada, France, Italy and Japan do not report some series around the beginning of our sample period. For these countries, we were able to obtain missing observations by splicing from old copies of OECD Bank Profitability Statistical Supplements. However, we are unable to confirm whether the aggregation methods of the OECD are consistent across their data sources.

Missing observations for 1980 were constructed by applying average growth for 3 preceding years to the data in 1981.

[12] This does not of course nullify the major benefits of Bankscope for undertaking cross sectional and panel research for individual banks (see Davis et al (2010) for example).

APPENDIX 2: METHODOLOGY FOR CALCULATING A PROXY FOR OFF-BALANCE SHEET ACTIVITY

Boyd and Gertler (1994) assume that all non-interest income is generated by securitizations and similar forms of assets that are stored off-balance sheet, and that the return on assets on and off-balance sheet are equal. These assumptions allows them to capitalize non-interest income using the balance sheet return in order to derive an estimate of OBS assets:

$$\Pi = I - E - P - N + Y \qquad (1a)$$

where Π are bank profits, I is interest income, E is interest expense, P is loan loss provisions, N is non-interest expense (i.e. staff and other operating costs shared across the institution) and Y is non-interest income. Balance sheet values for I, E and P cover only on-balance sheet activity whilst Π, N and Y cover all activities. In the decomposition below, the subscript o denotes off-balance sheet and b denotes on-balance sheet. If we assume rates of return are equal, we have the following identity of on-balance sheet (A_b) and implicit off-balance sheet assets (A_o), where the latter generates the non-interest income Y which can be decomposed into I_b , E_b and P_b.

$$(I_b - E_b - P_b - N_b)/A_b = (I_o - E_o - P_o - N_o)/A_o \qquad (2a)$$

Boyd and Gertler assume that there is symmetry between on-balance sheet assets and off-balance sheet activity in terms of non-interest expenses.

$$N_b/A_b = N_o/A_o \qquad (3a)$$

Combining the equations (2a) and (3a) and rearranging gives:

$$A_0 = A_b(I_b - E_b - P_b)/(I_b - E_b - P_b) \qquad (4a)$$

The denominator of (4a) is net interest income minus loan loss provisions, while the numerator is not directly observable. However Y is the net income generated by OBS activities before deducting non-interest expense, and substituting this into (4) and suppressing the on-balance sheet subscript, one may write

$$A_o = A_b\ [Y/(I - E - P)] \qquad (5a)$$

APPENDIX 3: CORRELATIONS

As Table A1 illustrates, correlations between the independent variables are low, thus reducing concern about multicollinearity. More systematically, as in Barrell et al (2010), we use the Breusch and Pagan (1980) test for cross section dependence to investigate the orthogonality of regressors. According to the test, the correlation coefficients are distributed as a standard normal variate where N is the cross section dimension and T is the time dimension

$$CD = (1/(N(N-1))^{**}(1/2)*(\sum_{i=1,N}\sum_{j=i+1, N-1}(T \rho_{ij}{}^{**2} - 1)$$

In neither case below is there any significant indication of correlation. In the first sub-table of contemporaneous variables, the standard normal deviate is -1.44 and in the case of the chosen lags it is -1.41 whereas the 95 percent two sided bound is 1.96. Hence we can be certain there are no interdependences in the data set.

Table A1: Correlations between independent variables

Contemporaneous correlations

	LEV	NLIQ	RHPG	CBR
NLIQ	-0.14			
RHPG	0.17	-0.13		
CBR	-0.22	-0.06	0.08	
DOFFTOON2	-0.02	-0.04	0.03	0.00

Correlations of chosen lags

	LEV(-1)	NLIQ(-1)	RHPG(-3)	CBR(-2)
NLIQ(-1)	-0.14			
RHPG(-3)	0.15	-0.20		
CBR(-2)	-0.22	-0.07	-0.03	
DOFFTOON2(-2)	-0.02	-0.05	-0.04	0.01

APPENDIX 4: ESTIMATION RESULTS FROM BARRELL ET AL (2010), FOR COMPARISON

Table A2: Logit estimation results over 1980-2008

Variable	Coefficient	z-Statistic
LEV(-1)	-0.342	-4.1
NLIQ(-1)	-0.113	-3.3
RHPG(-3)	0.079	2.4
CBR(-2)	-0.236	-2.8

Key: LEV= banks' unadjusted capital adequacy, NLIQ=banks narrow liquidity/asset ratio, RHPG= change in real residential property prices and CBR= current account to GDP ratio

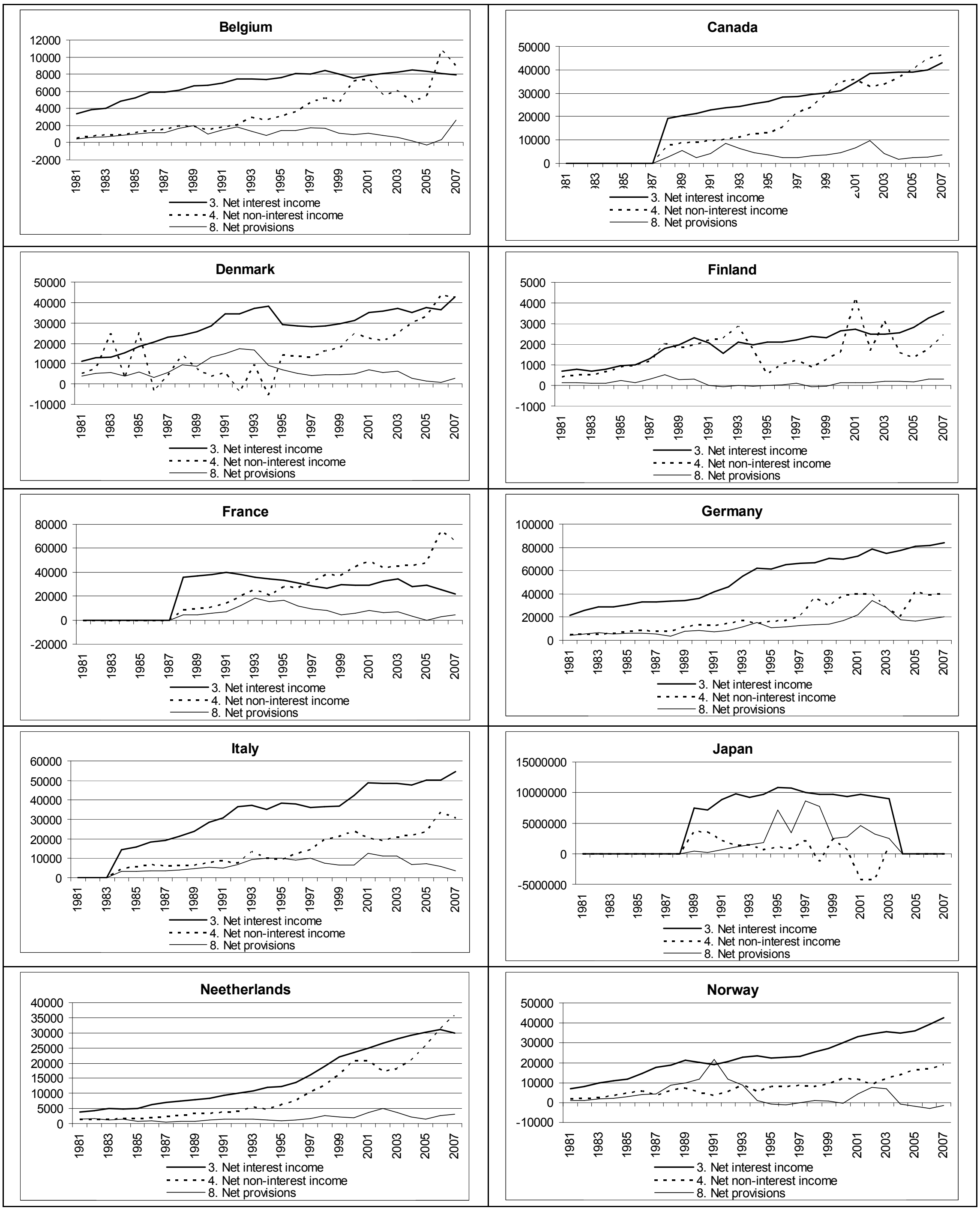
Table A3: In-sample model performance based on correct calls

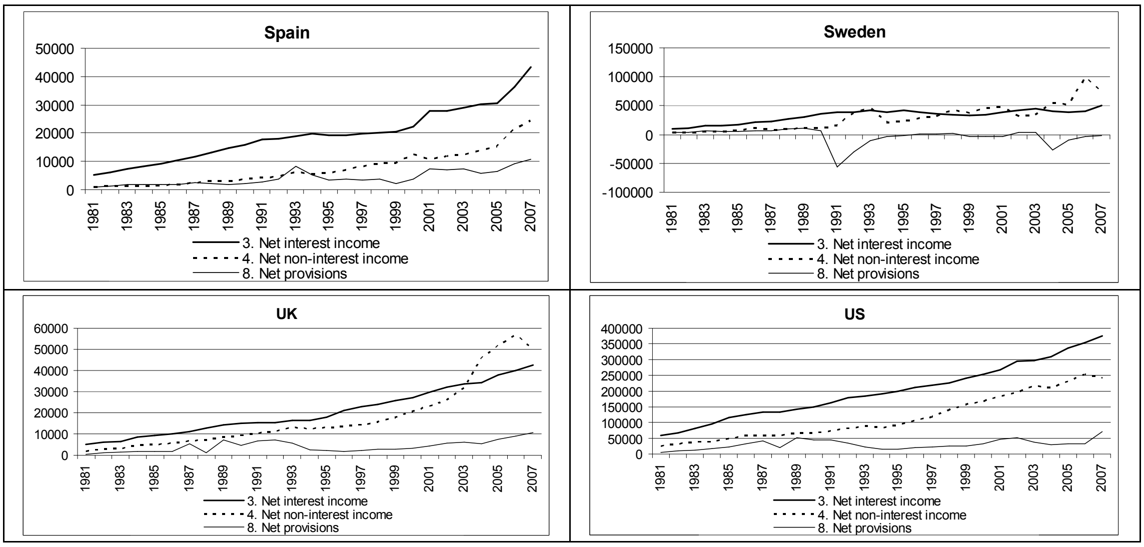
	Dep=0	Dep=1	Total
P(Dep=1)<=C	247	5	252
P(Dep=1)>C	97	15	112
Total	344	20	364
Correct	247	15	262
% Correct	71.80	75.00	71.98
% Incorrect	28.20	25.00	28.02

Note: threshold value is 0.0555

APPENDIX 5: DECOMPOSITION OF BALANCE SHEET INTO ITS COMPONENTS

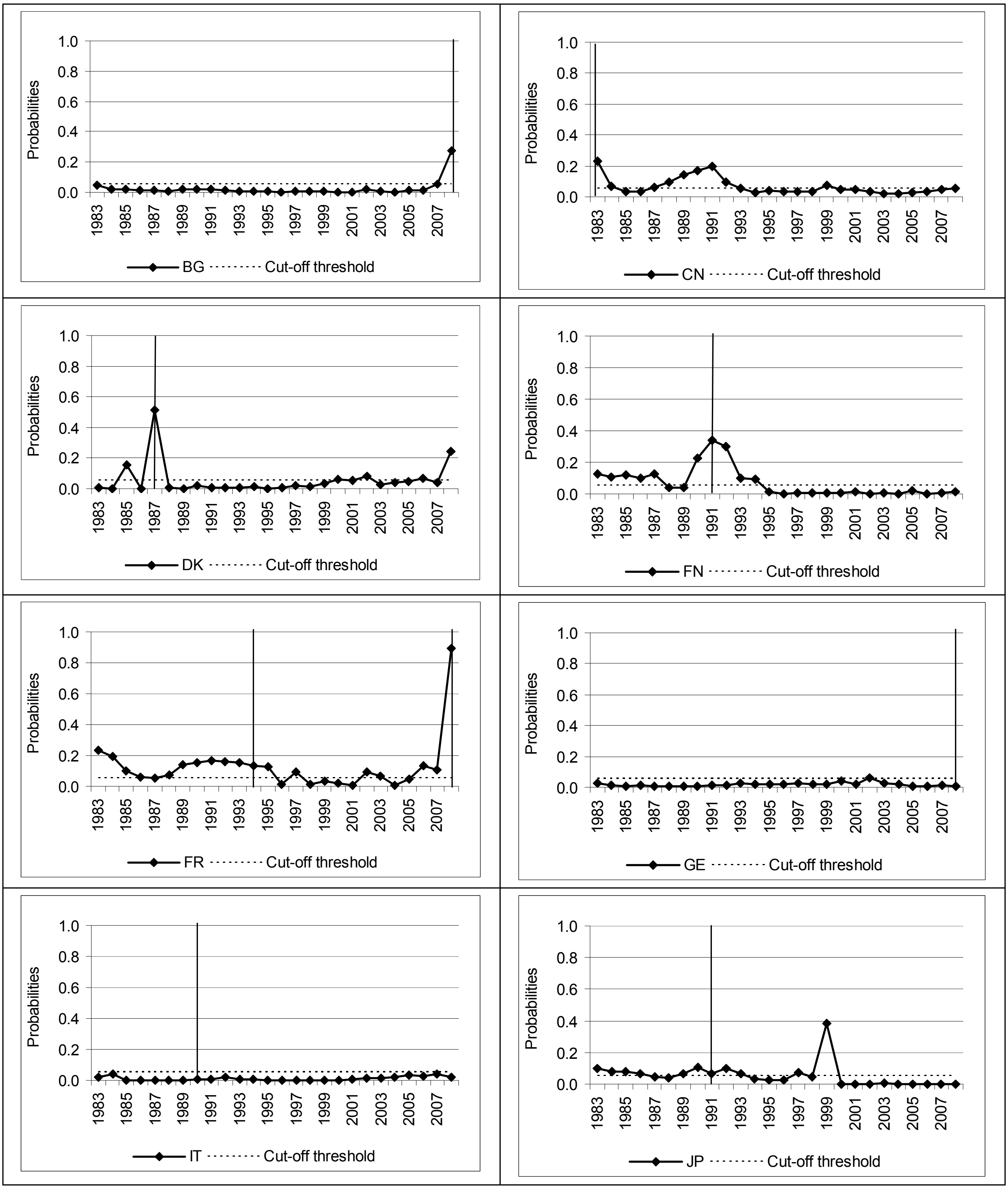
The charts below illustrate developments in net non-interest income, net interest income and net provision of banks (which generate the estimated ratio of off- to on balance sheet activities) in our sample countries over 1981-2007. The data source is the database of Bank Income Statement and Balance Sheets from the OECD. Statistics are reported at current prices in millions of national currency except for Euro zone members where figures are in millions of Euros.

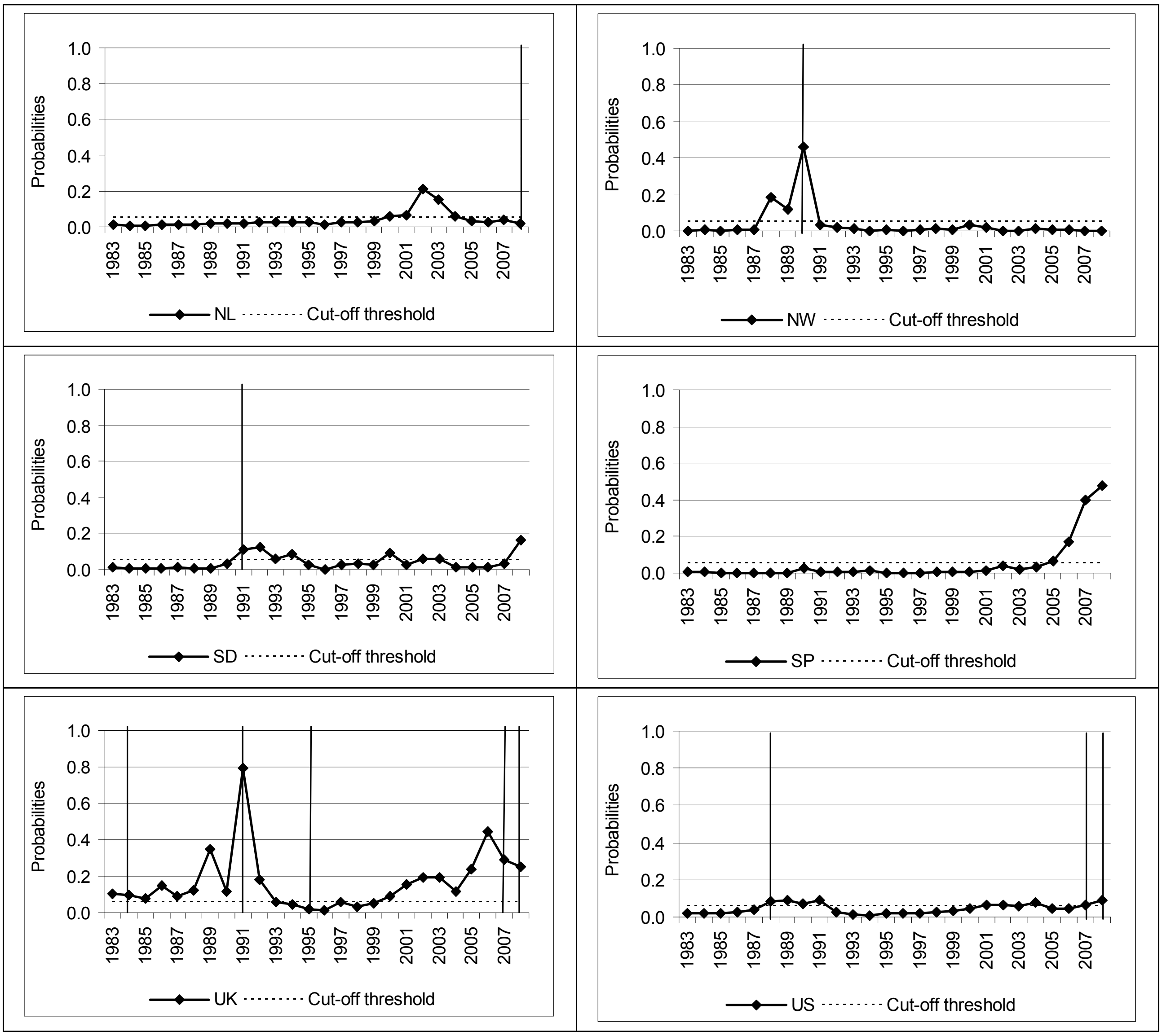



Spain
50000
40000
30000
20000
10000
0
1981 1983 1985 1987 1989 1991 1993 1995 1997 1999 2001 2003 2005 2007
3. Net interest income
4. Net non-interest income
8. Net provisions
Sweden
150000
100000
50000
0
-50000
-100000
1981 1983 1985 1987 1989 1991 1993 1995 1997 1999 2001 2003 2005 2007
3. Net interest income
4. Net non-interest income
8. Net provisions
UK
60000
50000
40000
30000
20000
10000
0
1981 1983 1985 1987 1989 1991 1993 1995 1997 1999 2001 2003 2005 2007
3. Net interest income
4. Net non-interest income
8. Net provisions
US
400000
350000
300000
250000
200000
150000
100000
50000
0
1981 1983 1985 1987 1989 1991 1993 1995 1997 1999 2001 2003 2005 2007
3. Net interest income
4. Net non-interest income
8. Net provisions

APPENDIX 6: IN-SAMPLE PROBABILITIES

The charts below illustrate in-sample probabilities of crises based on final estimation results for all countries in our sample (solid line depicts probabilities and the dashed line indicates the threshold value of 0.055).





Probabilities
NL
Cut-off threshold
NW
Cut-off threshold
SD
Cut-off threshold
SP
Cut-off threshold
UK
Cut-off threshold
US
Cut-off threshold

APPENDIX 7: CRISIS ONSET DATES

The table below lists banking crisis onset dates based on the definitions by World Bank (2003), Laeven and Valencia (2007) and Borio and Drehmann (2009)

Table A4: Crisis onset dates

Crisis	Date
Belgium	2008
Canada	1983
Denmark	1987
Finland	**1991**
France	1994, 2008
Germany	2008
Italy	1990
Japan	**1991**
Netherlands	2008
Norway	**1990**
Sweden	**1991**
UK	1984, 1991, 1995, **2007,** **2008**
US	**1988,** **2007,** **2008**

Note: bold indicates systemic banking crisis

APPENDIX 8: ADJUSTING THE OFF BALANCE SHEET PROXY TO REDUCE CRISIS PROBABILITIES TO THE SAMPLE MEAN

We adjusted our proxy for OBS activity by the amount necessary to decrease the crisis probability to our threshold value (0.055) in each country for every year in the sample. Table A5 illustrates the results of the exercise, with zeros indicating that the probability of a crisis in a country-year is already below 0.055 and no adjustment is necessary, while negative numbers illustrating a required reduction in the change of OBS activity[13]. Interpretation of the numbers is not straightforward as we are looking at the second derivative rather than directly at the movements in the ratios. But country by country and year by year comparisons still give us useful insights into risk exposures and increased vulnerability.

Based on the table, different groups of countries are immediately identifiable; first, those where none or almost no adjustment is required to OBS activity (Italy, Germany, Belgium); second, those which had banking crises historically and showed an elevated level of OBS exposures (Denmark, Finland, Sweden, Japan) and finally, countries where there was an increase in OBS vulnerabilities in the run up to the subprime crisis (France, Spain, the UK and the US). The last column of the table depicts the average adjustment for each year which was necessary across all the countries. We have two periods where OBS activity was excessive in relation to crisis risk, the largest adjustment was required for the period in the run up to current financial meltdown and the second one was over the 1990's when again many of the countries in the sample experienced banking crises. On the other hand we should emphasise that not all crises were related directly to OBS risk, as shown above – hence the adjustment shown below is not always warranted by the current situation.

Table A5: Required adjustment in the change of off- to on-balance sheet activity in order to keep crisis probability at in-sample mean level

	BG	CN	DK	FN	FR	GE	IT	JP	NL	NW	SD	SP	UK	US	mean
1985	0.00	0.00	**-0.53**	**-0.39**	**-0.30**	0.00	0.00	**-0.16**	0.00	0.00	0.00	0.00	**-0.18**	0.00	**-0.11**
1986	0.00	0.00	0.00	**-0.29**	**-0.03**	0.00	0.00	**-0.07**	0.00	0.00	0.00	0.00	**-0.49**	0.00	**-0.06**
1987	0.00	**-0.06**	**-1.32**	**-0.40**	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	**-0.23**	0.00	**-0.14**
1988	0.00	**-0.28**	0.00	0.00	**-0.12**	0.00	0.00	0.00	0.00	**-0.62**	0.00	0.00	**-0.38**	**-0.20**	**-0.11**
1989	0.00	**-0.48**	0.00	0.00	**-0.46**	0.00	0.00	**-0.08**	0.00	**-0.37**	0.00	0.00	**-1.01**	**-0.23**	**-0.19**
1990	0.00	**-0.57**	0.00	**-0.73**	**-0.52**	0.00	0.00	**-0.32**	0.00	**-1.21**	0.00	0.00	**-0.37**	**-0.11**	**-0.27**
1991	0.00	**-0.66**	0.00	**-0.99**	**-0.57**	0.00	0.00	**-0.07**	0.00	0.00	**-0.35**	0.00	**-1.90**	**-0.22**	**-0.34**
1992	0.00	**-0.25**	0.00	**-0.91**	**-0.54**	0.00	0.00	**-0.29**	0.00	0.00	**-0.40**	0.00	**-0.60**	0.00	**-0.21**
1993	0.00	0.00	0.00	**-0.30**	**-0.53**	0.00	0.00	**-0.08**	0.00	0.00	**-0.02**	0.00	**-0.05**	0.00	**-0.07**
1994	0.00	0.00	0.00	**-0.28**	**-0.43**	0.00	0.00	0.00	0.00	0.00	**-0.20**	0.00	0.00	0.00	**-0.07**
1995	0.00	0.00	0.00	0.00	**-0.41**	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	**-0.03**
1996	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
1997	0.00	0.00	0.00	0.00	**-0.26**	0.00	0.00	**-0.14**	0.00	0.00	0.00	0.00	0.00	0.00	**-0.03**
1998	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
1999	0.00	**-0.12**	0.00	0.00	0.00	0.00	0.00	**-1.07**	0.00	0.00	0.00	0.00	0.00	0.00	**-0.09**
2000	0.00	0.00	**-0.04**	0.00	0.00	0.00	0.00	0.00	**-0.04**	0.00	**-0.24**	0.00	**-0.25**	0.00	**-0.04**
2001	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	**-0.07**	0.00	0.00	0.00	**-0.52**	**-0.05**	**-0.05**
2002	0.00	0.00	**-0.20**	0.00	**-0.25**	**-0.06**	0.00	0.00	**-0.69**	0.00	**-0.05**	0.00	**-0.65**	**-0.06**	**-0.14**
2003	0.00	0.00	0.00	0.00	**-0.09**	0.00	0.00	0.00	**-0.51**	0.00	**-0.01**	0.00	**-0.63**	**-0.03**	**-0.09**
2004	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	**-0.04**	0.00	0.00	0.00	**-0.37**	**-0.14**	**-0.04**
2005	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	**-0.10**	**-0.77**	0.00	**-0.06**
2006	0.00	0.00	**-0.10**	0.00	**-0.43**	0.00	0.00	0.00	0.00	0.00	0.00	**-0.58**	**-1.19**	0.00	**-0.16**
2007	0.00	0.00	0.00	0.00	**-0.32**	0.00	0.00	0.00	0.00	0.00	0.00	**-1.10**	**-0.89**	**-0.07**	**-0.17**
2008	**-0.84**	0.00	**-0.77**	0.00	**-2.27**	0.00	0.00	0.00	0.00	0.00	**-0.55**	**-1.26**	**-0.80**	**-0.22**	**-0.48**

Note: data in the table should be multiplied by 100, in order to be interpreted in percentage point terms

[13] Years in the table refer to the date when probabilities are calculated, therefore as the *d(off to on)* variable is lagged twice, the actual adjustment required to it is referred to the period two years prior (for example, the probability for 1985 is calculated by taking into account *d(off to on)* in 1983, with the corresponding adjustment is referring to 1983 as well).

APPENDIX 9: AN ESTIMATE OF THE SHARE OF ON BALANCE SHEET ACTIVITY IN THE TOTAL.

Table A6: Estimate of the share of on balance sheet activity in the total

	Belgium	Canada	Denmark	Finland	France	Germany	Italy	Japan	Neths	Norway	Spain	Sweden	UK	US
1980	0.874	0.766	0.604	0.603	0.831	0.773	0.629	0.742	0.687	0.793	0.827	0.651	0.710	0.735
1981	0.846	0.762	0.575	0.568	0.821	0.773	0.660	0.763	0.644	0.783	0.836	0.655	0.719	0.683
1982	0.809	0.749	0.488	0.554	0.810	0.782	0.652	0.805	0.680	0.781	0.811	0.638	0.639	0.634
1983	0.776	0.754	0.242	0.534	0.798	0.795	0.718	0.803	0.707	0.772	0.817	0.635	0.608	0.637
1984	0.817	0.737	0.802	0.506	0.847	0.786	0.701	0.765	0.690	0.713	0.823	0.645	0.584	0.664
1985	0.783	0.726	0.332	0.457	0.829	0.755	0.689	0.728	0.708	0.668	0.811	0.588	0.609	0.648
1986	0.768	0.713	0.484	0.460	0.815	0.764	0.689	0.742	0.732	0.649	0.817	0.593	0.592	0.609
1987	0.747	0.672	0.805	0.464	0.788	0.769	0.717	0.671	0.736	0.780	0.788	0.669	0.466	0.614
1988	0.692	0.685	0.515	0.389	0.785	0.794	0.723	0.618	0.720	0.607	0.776	0.642	0.615	0.658
1989	0.706	0.633	0.703	0.478	0.779	0.692	0.745	0.658	0.683	0.602	0.803	0.639	0.451	0.583
1990	0.791	0.672	0.791	0.503	0.745	0.676	0.743	0.656	0.687	0.624	0.793	0.714	0.521	0.618
1991	0.751	0.655	0.771	0.482	0.701	0.723	0.747	0.788	0.665	0.608	0.781	0.861	0.458	0.613
1992	0.731	0.595	0.706	0.416	0.567	0.720	0.798	0.865	0.675	0.620	0.759	0.646	0.420	0.643
1993	0.673	0.614	0.684	0.421	0.407	0.716	0.678	0.837	0.631	0.615	0.619	0.532	0.446	0.649
1994	0.714	0.623	0.625	0.536	0.479	0.760	0.715	0.921	0.693	0.803	0.731	0.662	0.534	0.676
1995	0.662	0.635	0.609	0.789	0.374	0.756	0.750	0.768	0.647	0.745	0.731	0.661	0.539	0.661
1996	0.651	0.625	0.634	0.654	0.408	0.756	0.702	0.894	0.617	0.748	0.691	0.581	0.585	0.641
1997	0.571	0.543	0.647	0.637	0.369	0.722	0.644	0.393	0.578	0.721	0.667	0.529	0.595	0.624
1998	0.559	0.524	0.593	0.734	0.326	0.590	0.596	0.494	0.562	0.755	0.634	0.425	0.577	0.588
1999	0.596	0.474	0.584	0.653	0.403	0.658	0.585	0.751	0.549	0.737	0.657	0.490	0.564	0.577
2000	0.477	0.431	0.514	0.605	0.341	0.575	0.601	0.924	0.508	0.717	0.600	0.456	0.538	0.570
2001	0.476	0.440	0.553	0.374	0.296	0.558	0.637	0.894	0.507	0.713	0.658	0.474	0.521	0.546
2002	0.566	0.467	0.586	0.579	0.377	0.525	0.662	0.868	0.556	0.747	0.633	0.555	0.502	0.552
2003	0.558	0.503	0.555	0.421	0.377	0.625	0.637	0.843	0.573	0.706	0.633	0.541	0.464	0.547
2004	0.637	0.504	0.517	0.597	0.350	0.743	0.652	0.928	0.566	0.720	0.642	0.549	0.390	0.571
2005	0.611	0.478	0.522	0.664	0.379	0.603	0.646	0.867	0.529	0.695	0.615	0.482	0.370	0.570
2006	0.418	0.454	0.450	0.625	0.232	0.618	0.568	0.908	0.479	0.713	0.561	0.309	0.353	0.561
2007	0.372	0.460	0.483	0.572	0.204	0.617	0.622	0.971	0.431	0.700	0.575	0.424	0.389	0.555