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What Drives Systemic Bank Risk in Europe

The Balance Sheet Effect

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Non-Technical Summary

In this paper balance sheet variables most closely associated with systemic risk in European banks are identified. These variables are bank size, maturity-mismatch, market-to-book ratio and, to a lesser extent, non-performing loans. Evidence is found that such variables are significantly correlated with future realisations of systemic risk. This is particularly evident when systemic risk is measured using Adrian and Brunnermeier's (2016) Delta-CoVaR (ΔCoVaR) and not so evident using Brownlees and Engles (2010) Marginal Expected Shortfall (MES). ΔCoVaR measures a given institution's contribution to systemic risk while MES measures systemic exposure / fragility. For example, leverage is found to be a significant determinant of forward MES levels but not of ΔCoVaR, suggesting that high leverage renders a bank as being sensitive to a large common shock but its role in contagion propagation is less prominent

The focal point of most existing empirical work involving systemic risk measures has been US-based. For example, Adrian and Brunnermeier (2016) find that ΔCoVaR has early warning properties and that current balance sheet variables are strongly correlated with forward (i.e. future) levels of systemic risk. Laeven et al. (2015) also study ΔCoVaR using a cross-section of US banks just prior to the crisis. They find bank size (log of assets) to be the most important characteristic. Engle et al. (2014) study systemic risk in Europe using an instrument based on long-run MES. They do not consider any balance sheet factors and also do not take the direction of risk flow into account. Instead, they quantify the extent to which an institution's capital would be considered inadequate to absorb losses stemming from another catastrophic global shock.

This paper's focus is different. The primary objective is to clarify the relationship between balance sheet data and the systemic importance / fragility of banks. This is important because balance sheets reveal the investment decisions and risk-preferences of management. These can have, possibly unintended, adverse consequences when large financial shocks occur. The purpose of specifically-targeted macroprudential policy instruments is to mitigate the worst effects of such consequences. In this context establishing whether institutions have similar risk rankings regardless of the systemic risk measure involved is highly relevant, because such a finding could have policy-related implications. By ranking banks according to each of these measures it can be shown that systemically important institutions are not consistently identified. Evidence is presented showing that a cluster of large banks operating in one particular country contributes significantly to European systemic risk levels whereas a second cluster of banks, operating in a different country, appears most exposed to a large common financial shock. Thus, different risk channels need to be monitored via a variety of risk measures if financial stability is to be comprehensively evaluated.

Finally, it appears that ΔCoVaR tracks systemic risk accumulation in advance of a crisis whereas MES does not, at least from a balance sheet perspective. This clearly delineates the utility of ΔCoVaR as a potential early warning signal whereas systemic fragility measured via MES can best be identified using macroeconomic data (see Engle et al. (2014)).

What Drives Systemic Bank Risk in Europe The Balance Sheet Effect*

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Abstract

Since the 2008 global financial crisis (GFC) several systemic risk measures (SRMs) have gained traction in the literature. This paper examines whether Delta-CoVaR (ΔCoVaR) is relevant in the context of European banks and compares risk rankings against those found using marginal expected shortfall (MES). The analysis reveals that a cluster of large banks, operating in one particular country, is the principal contributor to financial system risk, if measured by ΔCoVaR. When the direction of risk flow is reversed, i.e. from the system to the institution (via MES), a second cluster of banks, headquartered in a different jurisdiction, would be most affected by a large and systemic financial shock. The analysis reveals that future realisations of systemic risk is strongly associated with institution size, maturity mismatch, non-performing loans and non-interest-to-interest-income ratios. However, in certain cases, the relationship depends upon the systemic risk measure used. For example, forward bank leverage appears correlated with MES but not with ΔCoVaR.

JEL Classification: [G01, G21, G28]

Keywords: [Systemic banking crisis, Systemic risk measurement, ΔCoVaR, MES, Bank Balance Sheet, Macroprudential policy]

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1 Introduction

Since the financial crisis significant academic and analyst attention has been geared towards the measurement of systemic banking risk, including contribution to and spillovers from systemic shocks, at the institution level. This risk becomes manifest as negative externalities affecting either the financial system, other institutions or the real economy, when a bank's failure appears imminent. Internal costs associated with bank failure have traditionally been quantified via measures such as credit-ratings, value-at-risk, Bank Z-Score and CAMELS scores to name but a few. However, the financial crisis exposed the "fallacy of composition" that the financial system as a whole must be safe if each individual bank appears stable. There is increasingly a consensus that new measures reflecting the systemic importance of institutions are required.

In recent years several such systemic risk measures (SRMs) have become prominent in the financial-crisis literature, two of which are examined in this paper. These are Delta-CoVaR (ΔCoVaR) and marginal expected shortfall (MES) (see Adrian and Brunnermeier (2016), Brownlees and Engle (2010) and Acharya et al. (2010)). Both measure systemic risk at the institution, rather than at the aggregate banking-sector, level. Some academics believe that systemic risk accumulates over time, particularly during the growth phase of the financial cycle when banks become significantly larger and/or more interconnected (see Brunnermeier et al. (2009), Diebold and Yilmaz (2012) and Schularick and Taylor (2012)). If this view is correct then such accumulations may be identified prior to the onset of a financial crisis. In terms of identifying the possible source(s) of such accumulations, one approach is to examine the composition of bank balance sheets, by testing the extent of the correlation between key management ratios and the institution's systemic risk levels as measured by various systemic risk measures. If current balance sheet-based ratios are shown to be significantly correlated with future systemic risk levels, then risk-mitigating steps can be taken in a timely fashion. The ex-post effectiveness of any policy-related action taken could also be ascertained, once empirical SRM-based benchmarks have been established. Before this can happen however, confidence in the measures' ability to consistently identify systemically important institutions will need to be secured.

In light of these considerations the following questions are explored in this paper; 1) whether systemically important financial institutions are consistently highlighted and ranked, regardless of the systemic risk measure involved and 2) the extent to which future systemic risk levels are correlated with current balance sheet composition.

The results associated with question 1) could provide evidence supporting the current designation of European banks as SIFIs or O-SIIs (see also Engle et al. (2014))[1] Such rankings would be further reinforced should they hold in a general sense, i.e. regardless of the risk measure used to establish them. In addition, it will clarify whether the direction of risk flow, be it to/from the institution, matters in terms of systemic importance. Guntay and Kupiec (2014) find that the use of different systemic risk mea-

[1] SIFI is an abbreviation for Systemically Important Financial Institution, O-SII an abbreviation for Other Systemically Important Institution. The Basel Committee for Banking Supervision has assigned SIFI / O-SII scores to institutions in the past. On occasion these rankings have been criticised on the basis that the methodologies by which rankings were allocated were opaque and absent the required degree of supporting evidence, see Benoit et al. (2016). A bank designated as a SIFI / O-SII is likely to face higher minimum capital and liquidity requirements due to its systemic importance.

sures leads to inconsistent rankings of US institutions but, to the author's knowledge, this has not been analysed in a European context. A finding of inconsistent inter-SRM rankings, using the two main alternative risk measures, does not necessarily mean that each measure is without merit. Instead each would be simply shown as capturing different aspects / channels of the prevailing systemic risk profile of the financial sector (see also Laeven et al. (2015)). Such a finding would therefore reinforce the need for regulators to gauge systemic risk using multiple systemic risk measures rather than relying upon one exclusively.

The evidence associated with question 2) should yield valuable supporting evidence for macroprudential policy-makers who set policies and define instruments so as to lessen the likelihood of and damage wrought by future crises.[2] Such instruments might be targeted at those factors which are consistently shown to be significantly correlated with systemic risk at the institution level. Adrian and Brunnermeier (2016) make the case that, as of 2006Q4, their measure of systemic risk, ΔCoVaR, identifies a high proportion of those financial institutions which subsequently failed during the financial crisis. They also find that systemic risk levels can be inferred from the investment and operational risk position adopted by banks in past periods via their historical balance sheet configurations. Thus, future systemic risk levels can be inferred from current balance sheet data. This feature of ΔCoVaR has not been contrasted with the relative performance of an alternative measure such as MES, particularly in a European context. Arsov et al. (2013) also find ΔCoVaR to be a predictor of future systemic risk levels both in the US as well as the euro area. This paper differs from theirs in that a wider sample of banks is included in the sample, including Greek as well as non euro area banks such as in the sample (e.g. UK and Norwegian banks). The main focus of the paper is on balance sheet characteristics, which are **amenable to macroprudential policy measures**, as explanatory variables. By comparison, Brownlees and Engle (2010) develop MES as a tool to help forecast capital shortfalls in the US banking system, with nine of their top 10 most systemically risky institutions (measured retrospectively) experiencing severe financial difficulty during the financial crisis. In a later study Engle et al. (2014) examine systemic risk in the euro area however their focus is on macroeconomic data rather than balance sheet data and they only report results for a single risk measure SRISK (which is based on long run MES).

The paper makes several contributions to the literature. First, it shows that different systemic risk measures yield different sets of risk rankings in European institutions, confirming earlier US-centric results. Furthermore, banks contributing toward systemic risk are clustered in a particular country, whereas those banks which are most exposed to a systemic event are headquartered in a different jurisdiction. Therefore the direction of systemic risk flow matters and is SRM-related. A second finding is that institution rankings tend to hold over time, with 2015 rankings very similar to average rankings measured over the full sample timeframe. Thus, policy interventions appear likely to have a long-lasting effect. Current and future realisations of systemic risk in European banks, measured ex-post via ΔCoVaR, are shown to be significantly correlated with balance sheet data. As was found earlier by Adrian and Brunnermeier (2016) and Laeven et al. (2015), the key variables appear to be; 1) bank size, 2) maturity mis-

[2] In this paper whenever a reference is made to risk this means systemic risk as measured by a systemic risk measure. Idiosyncratic risk, i.e. non-systemic risk will be explicitly referenced as such where appropriate.

match and 3) non-interest-to-income ratios (see also Brunnermeier et al. (2012)). These variables are statistically significantly correlated with systemic risk at leads of up to two years into the future. Taken together, these findings provide evidence supporting the targeted intervention by policy makers upon those factors which are most closely associated with elevated systemic risk levels. However, only limited evidence of a correlation between market-to-book ratios and systemic risk is found and no relationship at all is found between leverage and future ΔCoVaR levels. Non-performing loans are shown to be statistically significant regardless of systemic risk measure, although their marginal impact appears modest. Finally, the relationship between balance sheet data and MES is not as rich as is the case with ΔCoVaR. However, the analysis demonstrates a consistent relationship between systemic risk and institution size, regardless of the systemic risk measure involved. Thus, larger institutions pose a considerable systemic threat to the financial system, whether the risk emanates from the institution toward the system or vice versa. To a slightly lesser extent the same may be said for banks which have a greater proportion of their income derived from non-retail lending sources.

Overall the findings indicate that the use of MES as a guide to institution-driven systemic risk, despite the findings of Engle et al. (2014), is less compelling than is the case with ΔCoVaR, with possible macroprudential policy consequences. When formulating policy measures and assessing their effectiveness, regulators must be clear on the nature of the systemic risk being targeted, including its source, direction and marginal impact upon the vulnerability of the financial system as a whole.

The paper is organised as follows. The two systemic risk measures, including their method of calculation, are described in section 2. Data and summary statistics are outlined in section 3. Detailed results are presented in section 4. Robustness checks are covered in section 5 and section 6 concludes.

2 Systemic Risk Measures

Two important measures of systemic risk are examined in this paper, ΔCoVaR and MES.[3] ΔCoVaR measures changes in the tail (i.e. extreme adverse returns) risk of the financial system subsequent to a particular institution moving from generating normal (median) market returns to a scenario where it (i.e. the institution) experiences returns which breach its 5% value-at-risk threshold return level (see Adrian and Brunnermeier (2016) and Blancher et al. (2013)). Intuitively, the central idea behind ΔCoVaR is that an institution's distress has the potential to spill over to the financial system, causing that system to be exposed to greater losses in adverse circumstances than would have been the case had the institution been trading normally.

By contrast, MES measures average losses experienced by an institution on days when the financial system experiences large losses. Thus it signals the extent to which the institution is vulnerable to a general financial shock. Note the direction of risk flow is

[3] As the focus is primarily upon the predictive power of bank balance sheet characteristics, aggregate (i.e. at the financial system level) measures of systemic risk are not examined in this paper. This excludes such measures as volatility spillovers (see Diebold and Yilmaz (2012) and the composite index of systemic stress (CISS) (see Hollo et al. (2012)) which are not amenable to systemic risk analysis at the institutional level.

opposite to that measured by ΔCoVaR. MES captures a bank's exposure to common shocks, whereas ΔCoVaR is a contagion measure. Each systemic risk measure can be estimated at different frequencies, e.g. weekly, half-yearly or annually as required (see also Brownlees and Engle (2010) and Acharya et al. (2010)).

2.1 Measurement of ΔCoVaR and MES

Fundamental to the calculation of ΔCoVaR is the concept of value-at-risk (VaR). Formally this is defined as follows:

$$Probability(R^{\mathrm{i}} \leq VaR^{\mathrm{i}}_{\mathrm{q}}) = q \tag{1}$$

Here R^{i} is the level of return, based upon the growth rate of institution "i"'s share price and "q" is the confidence level (typically 1% or 5%).[4] So if q is chosen at 5% the above can be read as saying there is a 95% probability that institution "i" will not experience losses exceeding the value-at-risk threshold in the next trading or measurement period, based upon past returns. This threshold is termed the institution's VaR^{i}_{5}. Equation 1 can be estimated for each institution using the unconditional 5th percentile of returns measured over a sample timeframe. The median returns for each institution can be estimated using the 50th percentile and this threshold would be termed the institution's VaR^{i}_{50}.

Having calculated the VaR^{i}_{5} and the VaR^{i}_{50} for each institution the conditional value at risk (CoVaR) of the financial system can be calculated. This is defined as the financial system's index loss, with probability "q", conditional on the asset loss of bank "i" being at or exceeding a particular VaR measure (e.g. VaR^{i}_{5}). More formally this threshold is defined as follows:

$$Probability(R^{\mathrm{system}} \leq CoVaR^{\mathrm{system|i}}_{\mathrm{q}} | R^{\mathrm{i}} = VaR^{\mathrm{i}}_{\mathrm{q}}) = q \tag{2}$$

Two separate CoVaR measures may be estimated using regressions where the returns of the financial system are quantile-regressed against the $VaR^{\mathrm{i}}_{\mathrm{q}}$ of the institution and repeated again conditioned upon the VaR^{i}_{50} of the institution (see Blancher et al. (2013)). From these CoVARs the institution's ΔCoVaR is defined as follows:

$$\Delta CoVaR^{\mathrm{i}}_{\mathrm{q}} = CoVaR^{\mathrm{system|i,q}}_{\mathrm{q}} - CoVaR^{\mathrm{system|i,50}}_{\mathrm{q}} \tag{3}$$

Equation 3 represents what is defined as a static ΔCoVaR, which may be calculated over an arbitrary timeframe. It also facilitates the creation a time-varying counterpart which tracks the systemic risk contribution of the institution over a specific time-frame (e.g. quarterly) and which is defined per the following:

$$\Delta CoVaR^{\mathrm{i}}_{\mathrm{q,t}} = CoVaR^{\mathrm{system|i,q}}_{\mathrm{q,t}} - CoVaR^{\mathrm{system|i,50}}_{\mathrm{q,t}} \tag{4}$$

Equation 4 represents the ΔCoVaR definition described in the IMF's systemic risk monitoring toolkit. Also per their guidance (see Blancher et al. (2013)) controls for two state variables are included these being, i) weekly change in the yield curve and ii) the

[4] In earlier drafts of their paper, Adrian and Brunnermeier measure returns as the growth rate in the market value of assets, however in keeping with their most recent publication this paper relies on share price growth as the return measure.

Euribor-OIS spread, when performing the quantile regressions required to estimate the time-varying ΔCoVaR.[5]

MES is calculated as representing the average market value of equity lost by institution "i" on days when the financial system recorded losses of 2% or more.[6] Hence if the reference timeframe, "t", is set to a half-yearly measure (e.g. 2010H1) this yields ,

$$MES_{\mathrm{i,t}} = \frac{1}{T}\sum_{j=1}^{T} R_{\mathrm{i,j}} | R_{system,j} <= -2\% \tag{5}$$

In equation 5 "T" represents the number of days in the six month period "t" when the returns of the financial system were at least -2%.

3 Data and descriptive statistics

The Stoxx Europe 600 Bank index represents the financial system in this paper. However, please note that any portfolio of stocks or broad financial index may suffice, depending upon the researcher's preferred frame of reference. For the initial time-varying SRM calculations, losses and gains are measured based upon the weekly growth rate of the index over the period January 2000 to June 2015 inclusive. The sample comprises 30 banks, all of whom have a significant European presence.[7] A complete listing of the sample banks sample can be read from Table 1. Included are banks from Belgium, Germany, Italy, France, Austria, Sweden, Ireland, UK, Spain, Cyprus, Greece, Denmark and Finland. Thus the sample ought to be representative of the European banking system generally.

Having calculated weekly ΔCoVaR and MES data as per Equations 1 through 5, a panel of bank balance sheet data is formed, measured at half-yearly intervals and covering the period 2000-2015. The balance sheet variables of interest are suggested by the literature on systemic risk analysis (see Adrian and Brunnermeier (2016) and Brunnermeier et al. (2012)). Bank size (log of total assets), leverage, maturity mismatch, market-to-book ratio, non-performing loans, the ratio of non-interest income to interest income and expected default frequency are considered. These variables represent factors which earlier research has shown to be either determinants of systemic banking crises or to represent systemic risk sources in the period leading up to a crisis. (see also Hoggarth et al. (2005), Schularick and Taylor (2012), Goodhart et al. (2009), Blancher et al. (2013) and Bisias et al. (2012)).

3.1 Summary Statistics

Table 1 presents summary balance sheet data drawn from the sample's 30 banks. Mean and standard deviation statistics for each of bank size, leverage, maturity mismatch, market-to-book ratio, non-interest income to interest income and level of non-performing

[5] In this article use is made of weekly as well as half-yearly time-varying ΔCoVaR measures and q is set to 5%.

[6] Based upon the stylised fact that, historically, daily "market" losses are 2% or worse 5% of the time.

[7] Meaning a large proportion of their total revenue originates in European markets and/or their stated headquarters is within Europe.

Table 1: Summary Statistics - Balance Sheet Data (All Banks)

This table lists summary details for the main bank balance sheet related variables of interest. The sample comprises the following banks: Allied Irish Banks, Alpha, Anglo Irish Bank, Banca Carige S.p.A, Banco Bilbao Vizcaya Argentaria, Banco Santander, Bank of Cyprus, Bank of Ireland, Bankinter, Barclays, BNP Paribas, Commerzbank AG, Credito Emiliano S.p.A, Danske Bank A/S, Deutsche Bank AG, Dexia SA, DNB Bank Group, Erste Group Bank AG, Halifax Bank of Scotland Group, HSBC Banking Corporation, KBC Groep NV, Lloyds Banking Group PLC, Permanent TSB Bank, Piraeus Bank, Pohjola Bank Oyj, Royal Bank of Scotland Group, Skandinaviska Enskilda Banken, Societe Generale, Standard Chartered PLC and UniCredit S.p.A
Standard deviations in columns refer to intra-bank series whereas those listed at foot of the table refer to inter-bank variation.

Bank Name	**Avg. Log Size**	**Std. Dev.**	**Avg. Lev.**	**Std. Dev.**	**Mat. Miss.**	**Std. Dev.**	**Mkt. To Book**	**Std. Dev.**	**Non Int. to Inc.**	**Std. Dev.**	**Non Perf. Loan**	**Std. Dev.**	**Avg. Credit Growth**	**Std. Dev.**
B01	10.41	0.45	26.4	3.62	0.28	0.16	1.05	0.52	1.39	1.24	16031	6784	0.03	0.06
B02	10.9	0.48	25.93	3.96	0.34	0.16	13.27	5.05	1.48	0.79	26965	14145	0.05	0.11
B03	10.93	0.45	15.48	2.07	0.16	0.11	1.18	0.39	0.6	0.28	19713	15508	0.08	0.17
B04	7.24	0.39	17.89	2.75	0.3	0.09	1.42	0.67	1.02	0.57	495	500	0.06	0.07
B05	9.56	0.28	19.41	2.96	0.2	0.11	14.69	6.51	0.76	0.27	7367	6053	0.02	0.09
B06	10.7	0.31	39.83	11.93	0.11	0.05	0.86	0.38	1.05	0.71	7297	3189	0.06	0.11
B07	9.08	0.37	25.72	4.28	0.15	0.09	1.38	0.43	1.43	0.23	1407	700	0.03	0.09
B08	10.22	0.4	16.38	4.09	0.25	0.09	22.17	10.18	0.61	0.13	10363	8804	0.04	0.07
B09	8.71	0.34	22.42	5.87	0.13	0.07	1.55	1.12	0.74	0.52	10678	8673	0.03	0.07
B10	9.66	0.66	15.17	1.54	0.06	0.07	1.7	0.47	0.68	0.27	3227	1705	0.07	0.18
B11	10.68	0.53	28.85	7.2	0.25	0.08	1.25	0.74	1.05	0.41	13216	8173	0.05	0.11
B12	7.61	0.43	21.46	4.57	0.29	0.08	23.34	11.5	0.78	0.25	869	877	0.06	0.08
B13	9.08	0.66	18.76	5.83	0.11	0.14	12	4.88	0.54	0.1	11418	5588	0.08	0.26
B14	11.62	0.46	15.15	2.64	0.11	0.04	1.28	0.6	0.78	0.26	25274	12534	0.04	0.09
B15	9.79	0.4	32.43	7.29	0.3	0.08	0.69	0.4	0.81	0.35	14654	5727	0.02	0.21
B16	7.76	0.75	10.05	12.22	0.23	0.14	1.4	1.11	0.42	0.3	8964	10970	0.12	0.17
B17	10.17	0.65	25.26	6.94	0.1	0.11	1.94	1.06	0.81	0.8	22907	26318	0.08	0.37
B18	8.08	0.64	17.55	14.17	0.22	0.13	1.55	0.88	0.41	0.25	7102	7595	0.09	0.21
B19	10.41	0.73	16.8	1.92	0.22	0.05	1.15	0.68	0.88	0.2	38378	31225	0.08	0.33
B20	7.27	0.94	65.99	196.34	0.2	0.09	8.66	4.61	0.26	0.21	239	105	0.1	0.24
B21	11.01	0.71	26.59	47.29	0.17	0.09	1.71	4.77	0.9	0.21	25348	18857	0.1	0.42
B22	7.54	0.62	17.5	17.59	0.09	0.18	1.62	1.76	0.53	0.22	5481	2885	0.09	0.29
B23	7.54	3.1	-37.78	352.66	0.27	0.07	-0.07	26.15	-4.49	32.78	2445	1787	-0.03	0.17
B24	7.71	0.16	24.3	9.4	0.24	0.11	1.2	0.72	0.18	0.06	2047	3116	-0.07	0.08
B25	9.03	0.36	14.98	4.46	0.23	0.06	1.98	1.36	0.3	0.68	16257	15753	0.03	0.11
B26	7.33	0.62	16.81	3.08	0.19	0.19	16.02	3.82	2.13	1.29	28	15	0.09	0.12
B27	10.17	0.2	28.15	8.39	0.19	0.11	1.44	0.54	0.62	0.64	10565	2950	0.04	0.08
B28	9.65	0.21	28.32	4.78	0.2	0.04	1	0.41	0.42	0.36	11184	6616	0.18	0.65
B29	9.08	0.56	18.06	2.32	0.07	0.05	1.12	0.32	0.66	0.1	1811	1448	0.03	0.05
B30	7.73	0.4	12.09	4.48	0.14	0.07	16	6.74	0.96	0.69	1804	2045	0.05	0.07
Average	**9.22**		**20.87**		**0.19**		**5.15**		**0.62**		**10785**		**0.06**	
Minimum	**7.24**		**-37.78**		**0.06**		**-0.07**		**-4.49**		**28**			
Maximum	**11.62**		**65.99**		**0.34**		**23.34**		**2.13**		**38378**		**0.18**	
Std. Dev.	**1.36**		**15.21**		**0.08**		**6.96**		**1.05**		**9655**		**0.05**	

loans are presented, these being the core variables of interest. There is evidence of wide variation for each series on both an intra-bank as well as an inter-bank basis.

Thus the sample includes banks of different scale (log size ranges from 7.24 to 11.62), business model (non-interest income, leverage and credit growth), valuation (market-to-book), funding / liquidity profile (maturity mismatch), etc. Non-performing loans can be used to infer idiosyncratic risk but may also function as a proxy variable for management performance. Overall, fourteen separate banking sectors are represented by banks operating in both euro area as well as broader EU countries.

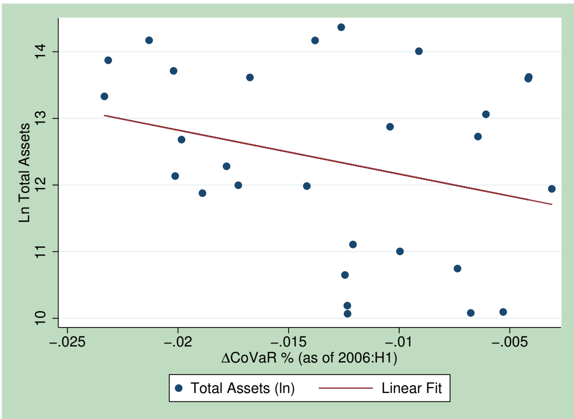

Fig. 1: ΔCoVaR vs Total Assets (2006:H1)

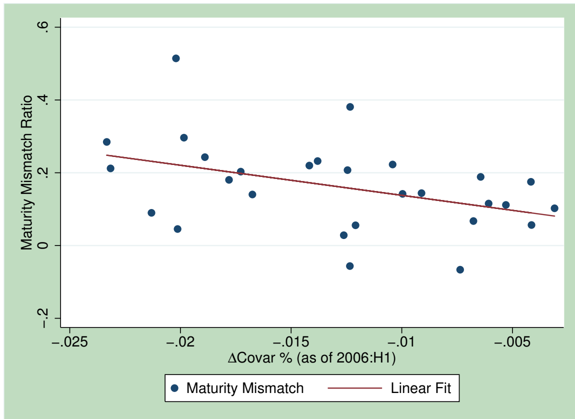

Fig. 2: ΔCoVaR vs Maturity Mismatch (2006:H1)

To motivate the analysis to follow prima facie evidence of the relationship between balance sheet variables and systemic risk is presented. For example both Adrian and Brunnermeier (2016) and Acharya et al. (2010) highlight the importance of institution size. Goodhart et al. (2009) stress the importance of liquidity imbalances. A scatter plot of these variables vis-à-vis ΔCoVaR as of 2006 (H1) is suggestive of similar relationships in a European context as can be seen via the downward sloping linear fits shown in Figures 1 and 2. As the systemic risk measures are decreasing in risk, larger institutions are seen as being associated with higher risk levels. Similarly, though to a lesser extent, the same is observed in relation to maturity mismatch. The significance, or otherwise, of such relationships in an econometric specification is now explored.

4 Results

Several figures illustrating certain systemic risk measure-specific attributes are presented initially, as well as their dynamic characteristics. Following this, detailed results are presented in a manner consistent with the two central questions posed in the Introduction.

4.1 Systemic Risk Summary

Dynamic weekly ΔCoVaR of the least and most systemically risky banks in the sample (Figure 3) are outlined, as well as the banks representing the inter-quartile range. Given that ΔCoVaR represents a measure of potential loss (negative returns), the lower the series plot the more systemically risky the institution is deemed to be. Thus, bank B01 is the most systemically risky according to ΔCoVaR and bank B30 the least risky on average, measured over the 2000-2015 timeframe.[8]

From 2007 week 30 onwards, there appears to be a negative shift in systemic risk levels generally until the crisis actually emerges in 2008 (shaded area), when risk levels are seen to be at their highest (represented by the deep trough in each series plotted). This is invariably true regardless of the bank involved. ΔCoVaR thus appears to track the increase in risk levels in the six to nine months leading up to the crisis regardless of host country or any other sector-related characteristic. Also note, rankings need not necessarily hold from week to week. For example bank B23 is, at times, deemed to be more systemically risky than bank B01, however the rankings represent sample averages over the estimation period 2000-2015 and, on this basis, B01 is most systemically risky overall.

It is apparent that banks' relative risk levels become more pronounced during periods of general financial distress, where bank B01 becomes noticeably more risky during the periods associated with the 2008 financial crisis as well as the subsequent sovereign debt crisis (circa 2010-2012). By way of contrast, bank B23's system risk profile behaves differently during these episodes.

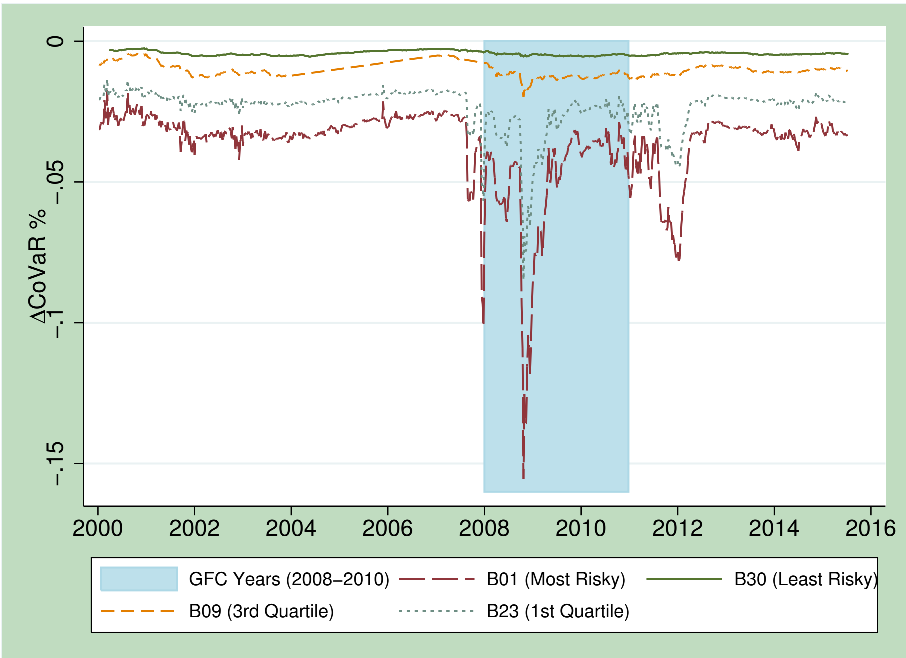

Fig. 3: ΔCoVaR - Systemic Risk Ranking Range, weekly data

The least and most systemically exposed institutions, according to MES, are plotted in Figures 4 and 5. Note that it is much more difficult, visually at least, to compare and contrast institution rankings. On average bank B16 appears to be the most exposed to a large financial system shock, particularly in the post-sovereign debt crisis period where large negative MES scores are consistently reported. By comparison the least exposed bank, bank B28, reflects several periods where stock price returns have actually been

[8] For confidentiality reasons bank identities are not revealed when describing systemic risk rankings. None of the paper's central findings is impacted by adopting this approach.

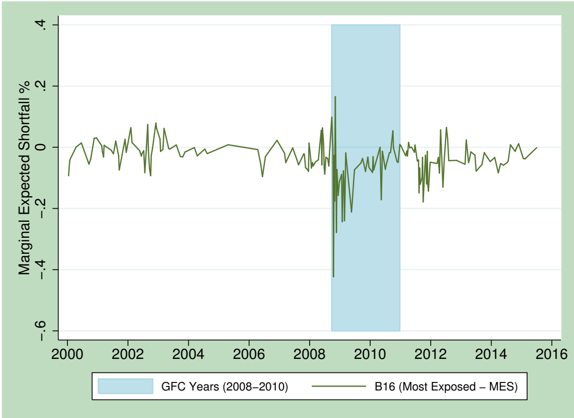

Fig. 4: Most Exposed Bank On Average - MES

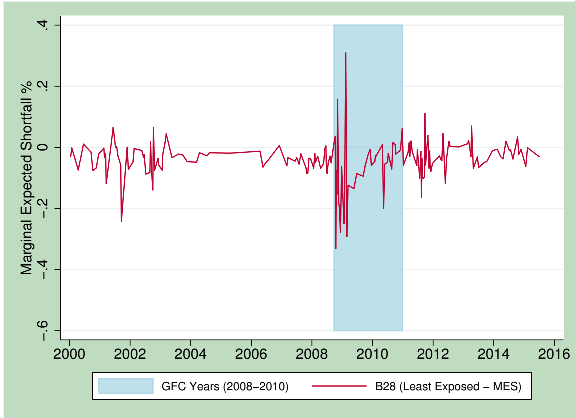

Fig. 5: Least Exposed Bank On Average - MES

positive, even though the financial system has performed poorly. Also, in those periods when B28 does demonstrate a negative reaction to financial system disturbances, such reactions are not as extreme as those shown by the most exposed bank.

Both ΔCoVaR and MES report much lower 2015 risk levels than were evident during the financial crisis. However there are several striking visual differences between the two SRM charts. The most important difference is that an institution's systemic risk rank depends upon the systemic risk measure used. The MES for B16 (most systemically fragile bank in the sample) remains negative for several years in the aftermath of the financial crisis and, apart from two occasions, stays so until the end of the sampling timeframe. Its average MES is -4.7%, whereas for bank B28 its average MES is a more modest -1%. This means that when the financial system experiences a large systemic shock, bank B16 suffers weekly losses of 4.7% on average. A shock is defined as meaning that there was at least one day, during the week in question, when the financial system recorded a loss of 2% or more.

Rankings aside, there are other clear differences worth noting. ΔCoVaR values are invariably negative, even for the least systemically risky institution. By comparison MES is frequently reported with positive values, even for the most exposed institution. Thus there are times when banks appear less exposed to the consequences of a systemic financial shock, even when they might pose a systemic threat themselves.

Furthermore, MES does not appear to reflect any systemic risk accumulation in advance of the financial crisis. Evidence for this can be seen via the oscillation of the MES series between positive (no exposure) and negative values. This behaviour remains visible even during the period when the global financial crisis was at its height, thus a leading signal of impending difficulty is difficult to discern using MES as a gauge.

There is one possible exception to this conclusion worth mentioning. Both MES graphs report banks as being at very low exposure levels over the period 2004-2006, a pattern which is common to all banks in the sample. In the case of the Irish banks, the local economy was booming during these years and a housing bubble forming. The financial system recorded very few days, if any, when large losses were reported. As the crisis unfolded MES levels became increasingly more volatile. This may be a feature peculiar to this particular sample but may also signal, in a more general sense, that a period of calm is seen to precede a systemic crisis as others have suggested (see Brownlees et al. (2011) and Dabrowski (2010)). Further research with much larger samples, spanning multiple crises, may be required to tease out this potential early warning system characteristic in more detail.

4.2 Consistent Identification of Systemically Important Banks

The answer to the first central question, posed in the Introduction, is suggested by the Figures presented above. By tabulating the average quarterly systemic risk rankings of banks (see Table 2), further evidence against the consistent, SRM-independent, identification of systemically important institutions is obtained.

For each of MES and ΔCoVaR, there is little, if any, cross-SRM consistency in ranking terms. The three most systemically risky banks, on average, according to ΔCoVaR have MES ranks of 22, 6 and 14 respectively, whereas the three most systemically fragile banks according to MES have ΔCoVaR ranks of 16, 15 and 11 respectively on average. This diversity may be explained by taking the view that each systemic risk measure captures different facets of systemic risk, emanating from a variety of channels and depending fundamentally upon the direction of risk flow, as was alluded to earlier. Having selected alternatives to the Stoxx Europe 600 Bank index to represent alternative financial systems, ΔCoVaR values and subsequent institutional rankings are found to be sensitive to this choice.[9] However, regardless of the choice of financial system index, significant systemic risk measure-related variation in terms of systemically important institution identification can be seen.

Though they are not named it can be revealed that the two most systemically risky banks according to ΔCoVaR are relatively large institutions operating in the same EU country. Likewise, the most exposed institutions according to MES, also operate in a single country. However the most risky jurisdiction according to ΔCoVaR is not the same as that which hosts the leading MES-ranked banks. As a consequence, national authorities must be cognizant of any potential shock-related spillover effects that may propagate from jurisdiction to jurisdiction.

The sample's final half-yearly estimates for each systemic risk measure (2015:H1) are also reported in Table 2. In general, although there is some movement in rankings based upon sample averages, the same banks are consistently reported as being most systemically risky according to the corresponding systemic risk measure. This indicates that banks, operating in one particular country, continue to pose the greatest systemic threat to the financial system on an ongoing basis, but that banks in a different jurisdiction are most exposed to the effects of any large or systemic shock. It also indicates that what makes an institution systemically important at a given point in time is likely to persist in the medium-to-long term.

4.3 Future systemic risk and current balance sheet data

One of the key aims of this paper is to test the extent to which future (i.e. in-sample predicted) realisations of systemic risk can be explained by current balance sheet composition. This goal is framed as question 2 in the Introduction.

[9] These results are not reported but are available upon request

Table 2: Systemic Risk Rankings - (2000-2015)

This table lists the sample banks in order of their systemic risk under both the ΔCoVaR and MES assessments. These are listed in ascending order with the riskiest bank listed first according to ΔCoVaR. Each bank's MES ranking alongside other attributes including 2015 market capitalisation is shown and size (share of total portfolio assets). Note, balance sheet data for failed/acquired banks relate to 2009 H2 timeframe prior to resolution/acquisition. Also note, current ΔCoVaR and MES rankings for 2015 are in two rightmost columns respectively. The most exposed bank according to MES has an MES rank of 1 (bank B16), the least exposed has an MES rank of 30 (bank B28).

	Avg. Rank ΔCoVaR	Bank Code	Avg. Rank MES	VaR Rank	Portfolio Weight (asset %)	ΔCoVaR Rank 2015	MES Rank 2015
←— Declining in ΔCoVaR Risk Level —→	1	B01	22	10	7.39	1	10
	2	B02	6	18	11.62	2	6
	3	B03	14	20	7.28	3	3
	4	B04	21	13	0.19	4	26
	5	B05	5	12	1.40	7	19
	6	B06	4	19	9.21	6	17
	7	B07	11	24	1.62	8	20
	8	B08	8	27	3.75	5	8
	9	B09	9	8	0.71	9	5
	10	B10	17	25	3.39	11	14
	11	B11	3	15	9.17	12	13
	12	B12	18	14	0.32	10	7
	13	B13	16	21	1.07	13	16
	14	B14	23	30	13.98	14	24
	15	B15	2	7	3.05	15	9
	16	B16	1	3	0.47	16	1
	17	B17	19	23	6.31	17	21
	18	B18	13	4	0.38	18	2
	19	B19	10	17	4.76	19	4
	20	B20	29	9	-	-	-
	21	B21	7	11	7.39	20	11
	22	B22	12	6	0.14	21	18
	23	B23	27	1	1.31	22	27
	24	B24	15	2	0.18	23	12
	25	B25	20	5	0.58	24	15
	26	B26	24	28	-	-	25
	27	B27	28	26	-	-	-
	28	B28	30	29	2.52	25	22
	29	B29	25	22	1.64	26	23
	30	B30	26	16	0.17	27	28

This is highly relevant from a macroprudential policy perspective given that future systemic risk may stem from the business investment decisions made by bank executives, with systemic risk accumulating as a result (perhaps inadvertently). Thus, this analysis can direct macroprudential policy instruments toward those balance sheet factors most closely associated with systemic risk. These factors can be benchmarked on a peer-to-peer basis and reviewed by regulators **prior** to the onset of a crisis. Institutional systemic risk measures might also be appraised on a country-by-country basis to establish the most systemically risky institutions/jurisdictions and to calibrate policy instruments (e.g. counter-cyclical or O-SII buffers) if supervisors so desire.

Figures 1 and 2 present initial evidence that such relationships might exist. Also, Table 2 strengthens this view in that the majority of the sample's larger banks are seen to appear in the top half of the systemic risk rankings (see also Laeven et al. (2015)).

A more comprehensive analysis is carried out using a panel data specification with fixed effects to control for inherent intra-bank differences. No time-invariant factor is therefore permitted in the regressions, due to model-collinearity with the bank fixed effects. A trend variable to control for half-year related confounding effects is included. Following the guidelines set forth in Adrian and Brunnermeier (2016) the systemic risk measures are re-estimated at half-yearly frequencies to align with bank annual report data. Quantile regressions are limited to the 2000-2010 period because of concerns that heightened systemic risk measures during the period 2008-2013 might dominate any relationships. Year 2010 is included on the basis that balance sheet data lagged back two years to 2008 is required for this analysis. Hence, the following models are estimated;

$$\Delta CoVaR_{\mathrm{i,t+h}} = \alpha + \beta Z_{\mathrm{i,t}} + \zeta Bank_{\mathrm{i}} + \delta Halfyear + \epsilon_{\mathrm{i,t}} \qquad (6)$$

$$MES_{\mathrm{i,t+h}} = \alpha + \beta Z_{\mathrm{i,t}} + \zeta Bank_{\mathrm{i}} + \delta Halfyear + \epsilon_{\mathrm{i,t}} \qquad (7)$$

Here, future values (i.e. forward lags) of both ΔCoVaR and MES are regressed against balance sheet variables. That is, separate models, one per forward lag, i.e. "h", for each of the systemic risk measures are estimated at 6, 12, 18 and 24 months ahead;

The results of this analysis are presented in Table 3 below. The most significant variable is institution size, where it appears as significant in ΔCoVaR regressions (2) to (4)) as well as MES regressions (6) to (8). The negative coefficients indicate that systemic risk is increasing in the variable. Bank size has been flagged in the literature as one of the most important reasons for the proliferation of the 2008 financial crisis. Brunnermeier et al. (2009) provide a detailed explanation of the dynamics involved during the onset of the crisis which they maintain was driven by i) bank size, ii) maturity mismatch and iii) mark-to-market accounting rules.

Table 3: Forward Systemic Risk vs Balance Sheet Composition

This table illustrates the relationship between current bank balance sheet variables and future levels of systemic risk measured by ΔCoVaR and MES. 6 month, 1 year, 18 month and 2 year forward levels of systemic risk are shown for each SRM. All sample banks are included in this analysis with data covering the period 2000H1 to 2010H2, i.e. half yearly data. The regression model is panel based sorted by bank and half-year with bank fixed effects and with a control for trend. Standard errors are listed below the coefficients. Statistical significance of coefficients are denoted by ***, ** and * at the 1%, 5% and 10% levels respectively.

	ΔCoVaR				MES			
	6-mths ahead	12-mths ahead	18-mths ahead	24-mths ahead	6-mths ahead	12-mths ahead	18-mths ahead	24-mths ahead
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Institution Size	-0.002	-0.008**	-0.012***	-0.015***	-0.006	-0.053***	-0.051***	-0.062***
	(0.003)	(0.003)	(0.004)	(0.004)	(0.014)	(0.015)	(0.017)	(0.014)
Maturity Mismatch	-0.001	-0.015**	-0.015**	-0.018**	-0.011	0.014	-0.048	-0.020
	(0.006)	(0.007)	(0.007)	(0.008)	(0.031)	(0.032)	(0.034)	(0.028)
Non-performing Loans	0.000	0.000**	0.000**	0.000*	0.000	0.000	0.000	0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Expected Default Frequency	-0.015***	-0.002	0.006	0.019***	-0.010*	-0.004	-0.008	0.055*
	(0.005)	(0.007)	(0.006)	(0.007)	(0.006)	(0.007)	(0.007)	(0.028)
Non-interest to Interest Income Ratio	-0.000	-0.001	-0.002**	-0.001	-0.001	0.008*	0.014***	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.004)	(0.004)	(0.005)	(0.004)
Market to Book Ratio	0.000*	0.000	-0.000	-0.000	0.001	-0.000	-0.001	-0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Leverage	-0.000	0.000	0.000	0.000	-0.001**	0.002***	0.001**	0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Half-year Trend	-0.001***	-0.001***	-0.001**	-0.001**	-0.002	0.001	-0.001	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Constant	0.082***	0.158***	0.175***	0.214***	0.206*	0.506***	0.625***	0.690***
	(0.023)	(0.027)	(0.028)	(0.032)	(0.113)	(0.125)	(0.140)	(0.113)
Observations	270	247	220	199	339	314	290	264
R-squared	0.303	0.344	0.353	0.413	0.106	0.127	0.186	0.263
Number of banks	28	28	28	27	30	29	29	28
Degrees of Freedom	35	35	35	34	37	36	36	35
Model P-value	0	0	0	0	0	0	0	0

In the years preceding the financial crisis large banks had become increasingly reliant on short-term funding of their ever-increasing assets, leading to a deterioration in their maturity mismatch values. A significant proportion of short-term funds were provided by fellow banks. Throughout 2007-2008, banks became increasingly concerned about their potential inter-bank exposures and ceased making funds available to one another, a situation termed the ”credit crunch”.

With little or no short-term funding available, banks had no choice but to de-leverage or face insolvency. However, many banks found themselves with the requirement to offload assets simultaneously, leading to a large fall in asset values. Mark-to-market accounting rules require banks to recognise reduced asset values immediately. Capital is absorbed as losses mount and, to avoid insolvency and/or remain regulatory compliant, further de-leveraging becomes necessary.

More generally, because banks may act in unison to protect their own self-interest by de-leveraging during periods of low/no market funding conditions there can follow a liquidity-run in the banking system as a whole. This in turn can precipitate a fire-sale of assets which, in extreme circumstances, may lead to a systemic banking crisis. The larger the institution the greater the degree of de-leveraging potentially involved. What was intended to be a risk-reduction provision (i.e. mark-to-market accounting rules) actually has had the opposite effect to that intended when banks ”herd” in this way.

A notable feature of table 3 concerns the number of significant variables reported as significantly correlated with systemic risk, particularly in the case of ΔCoVaR. This fact, coupled with the higher R-squared values lends support to the contention that ΔCoVaR has useful forward-looking properties, reflecting systemic risk-inducing characteristics prevalent in balance sheets (see Adrian and Brunnermeier (2016)). Taking the direction of risk flow into account it would appear that balance sheets are informative as regards systemic risk flowing from banks towards the system as a whole as measured by ΔCoVaR, but are somewhat less informative regarding financial system shock exposures as measured by MES.

In the case of ΔCoVaR the most meaningful balance sheet factors appear to be institution size, maturity mismatch (over-reliance on short-term funding) non-performing loan levels and expected default frequency. To a lesser extent business model (ratio of income derived from non-traditional lending sources) and market over-valuation are occasionally significant.

To estimate the potential financial system losses involved the risk factors’ marginal effects on systemic risk exposures must be considered. In the case of bank size, larger institutions pose more of a systemic risk where a 1% increase in the average size of an institution is associated with a 1.5 basis point increase in systemic risk levels, two years ahead, at the 95% confidence level. The average institution size over the sample timeframe is €514bn. Therefore an institutional size increase of approximately €5bn is associated with a 1.5 basis point worsening of the 95% conditional value-at-risk of the Stoxx Europe 600 Bank index - should that institution itself become troubled in the future. The market cap of this index is €1.3 trillion (as of August 2015) so this equates to a conditional value-at-risk threshold increase of circa €195m in market cap terms.[10] Similar effects derive from higher levels of maturity mismatch and, as was

[10] Data source for the Stoxx Europe 600 Bank index is from www.stoxx.com

found earlier by Brunnermeier et al. (2012), the proportion of income derived from non-lending sources.

Further evidence supporting the ability of ΔCoVaR to reflect systemic risk accumulation in advance of crises is seen in the half-year trend variable where significant coefficients are reported. However, this effect is not present in the case of the MES measure. That said, there are two variables on the MES (regressions (5) to (8)) side of the table which appear to be more correlated with MES than is seen whenever ΔCoVaR is utilised (regressions (1) to (4)). These are leverage and the ratio of non-interest income over interest income. Leverage appears to matter more when the financial system experiences a large shock but does not appear to be a significant factor in terms of the systemic risk contribution of the institution. This finding is contrary to that of Adrian and Brunnermeier (2016) and Homar et al. (2016), however this may be due to a relatively small sample size. Finally, it appears that non-performing loan levels are less significant than anticipated and have very small marginal effects. They also have the "wrong" sign in that higher levels appear to be associated with lower levels of systemic risk, contrary to expectations.

These balance sheet variables are found to be associated with system risk levels up to two years in the future. This suggests that positive action may, in certain cases, be undertaken to reduce future risk levels even if the factor itself takes time to adjust (e.g. institution size). The longevity of the relationships suggest that remedial actions by management or supervisors ought to have a lasting effect on systemic risk levels.

5 Robustness Checks

In this section several criticisms of the systemic risk measures themselves are considered, in addition to the justification of certain parameter choices.

5.1 The effectiveness of the SRMs as risk monitoring tools

Some academics have been critical of systemic risk measures on the basis that they provide relatively little new information over and above what might have been available via traditional risk measures. For example Guntay and Kupiec (2014) argue that ΔCoVaR is merely a scaled representation of the institutions' value-at-risk. Indeed Adrian and Brunnermeier (2016) acknowledge the tight correlation that exists between VaR and time-varying ΔCoVaR. Other criticisms (see Benoit et al. (2013)) are that the new measures are capturing **systematic** risk and that MES, for example, could be easily replaced by Market Beta.[11]

MES differs from Beta in several important ways. Firstly the MES "market" is only limited to the researcher's choice of financial system whereas Beta is more constrained. For example, the researcher may choose a portfolio of stocks for his/her choice of market

[11] Market Beta is a numeric value measuring the responsiveness of a security to changes in a stock market generally. A score of greater than 1 implies the security reacts strongly to market fluctuations, a score of less than 1 implies that the security has a more muted response to changing market sentiment. Investors expect higher returns from securities with a Beta of greater than 1 because of the perceived higher (than market) risk, whereas securities with low Betas can be used to reduce the overall risk profile of a portfolio of investments.

or financial system, whereas Beta is typically calculated with respect to the main stock market of the firm's home country. Secondly both ΔCoVaR and MES measure sensitivity to extreme tail-events in the returns distribution of the chosen financial system whereas Beta characterises the full-distribution relationship between the institution's stock returns and a specific market index. Such differences may be subtle but they are important.

Given that ΔCoVaR derives from two conditional value-at-risk measures its strong correlation with value-at-risk is unsurprising. However, repeating the analysis of Adrian and Brunnermeier (2016) in Figure 6 below it can be seen that, in a cross sectional setting, there does not seem to be any systematic relationship evident. Certainly there is nothing suggesting a one-to-one relationship between systemic risk and idiosyncratic risk one would expect to see were the two instruments to capture identical risks at the institution level. Thus, what makes an institution idiosyncratically risky does not necessarily translate into rendering the institution either systemically important or fragile. This is a fundamental distinction, investors are interested in measuring whether their investments represent value for money given the risk profile of the firm involved (i.e. VaR). However, bank supervisors and/or macroprudential policy makers are interested in the repercussions of an institution's failure upon the financial system generally. ΔCoVaR yields an indication of this, even if VaR may not.

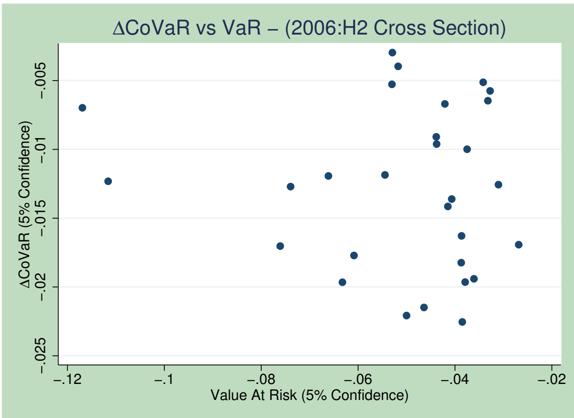

Fig. 6: ΔCoVaR versus Value-At-Risk

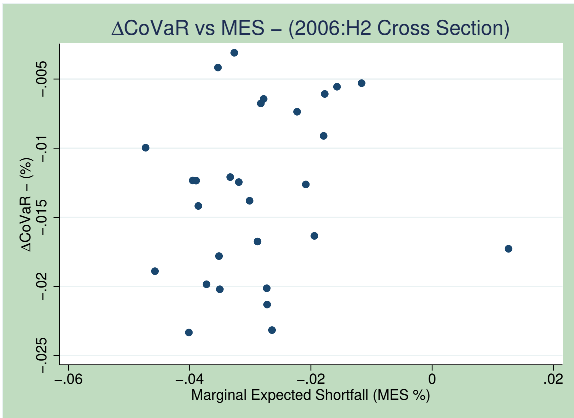

Fig. 7: ΔCoVaR versus MES

The fact that VaR and ΔCoVaR co-move may be of interest, but it is the scale and extent of the ΔCoVaR movement in particular that informs about the scale of any widespread financial system losses and it is the latter that concerns those responsible for safeguarding the financial system.

Figure 7 reinforces the view discussed in the context of the SRM rankings (cf. table 2) that MES and ΔCoVaR are non-interchangeable. In the cross-section there is no obvious systematic relationship between the two SRMs. That there are inter-bank differences in reporting from measure to measure highlights the need for comprehensive systemic risk measurement by regulatory authorities. This extends to the use of composite / aggregate indicators of financial stress (e.g. the "CISS" index) in addition to institution-based SRMs (see also Diebold and Yilmaz (2012) and Hollo et al. (2012)). Only then, assuming uniform reports of low systemic risk are reported, can one be reasonably confident that a large-scale banking crisis appears unlikely.

In relation to the calculation of time-varying ∆CoVaR we have found that the quantile regression results are sensitive to the choice both of the financial system index as well as to the choice of control variables mentioned after Equation 2.[12] An issue arises in that Adrian and Brunnermeier (2016) make use of control variables such as the VIX index, real-estate company returns, weekly equity returns of a broad index of shares as well as several liquidity and yield curve spread measures. By contrast, the IMF's systemic risk monitoring toolkit (see Blancher et al. (2013)) recommends a much smaller set of control variables limited to the Libor-OIS spread and the weekly change in the yield curve (defined as the spread between the 10-year Treasury bond yield and the 3-month Treasury bill yield). The data on European banks results in much fewer observations than in Adrian and Brunnermeier (2016) so IMF guidance is followed in terms of limiting the choice of control variables. However, results must be interpreted accordingly.

A Hausman test verifying the choice of a bank fixed-effects panel model, rather than a random-effects specification, has been utilised. The regression results are not driven by any one bank in particular as revealed via the elimination of one bank at a time from the regressions. The coefficients change marginally but statistically significant variables and their corresponding signs do not. The data is also analysed to see if the relationship between balance sheet and systemic risk holds at the country level. By limiting the sample to i) UK banks and then ii) Irish banks any striking differences might be observed. In the case of UK banks the same variables are reported as significant, although the effects are weaker in the case of Irish banks. These results are not reported as the sample sizes are greatly reduced and may not be fully representative. As the time series grow more analysis at the country level will be possible and this is noted as an area for future research.

The half-yearly ∆CoVaR values are estimated in a variety of ways including averaging over the 26 weeks in a half-year, a scaled version of the same metric according to the square root of time rule (as used in value-at-risk calculations, see Hull (2006)) and according to half-yearly stock returns (as presented above). The same statistical relationships were observed regardless of calculation method.

Finally the half-yearly variable (see Equations 6 and 7) were replaced with a time fixed-effects alternative, (i.e. one dummy variable per half year). As expected, the four half-yearly dummies covering 2009 and 2010 are all negative and statistically significant at the 1% level of significance. The size variable loses explanatory power in these circumstances, however this outcome does not detract from the main finding with respect to institution size, which is that larger banks were more systemically risky as the crisis unfolded. This effect is not observed in Adrian and Brunnermeier (2016), however, their research benefits from a much larger sample, representing the main reason for any differences in the results reported.

6 Conclusion

In this paper two systemic risk measures, ∆CoVaR and MES, are examined at the institution level. The paper shows whether the identification of banks as systemically important remains robust to the choice of systemic risk measure or, given their respec-

[12] These results are not reported but are available upon request.

tive properties, whether the direction of risk flow matters. The relationship between future realisations of systemic risk levels and current balance sheet composition are also examined, with a view to identifying those factors most closely associated with financial system risk.

The choice of systemic risk measure makes a difference in terms of identifying systemically risky institutions. This finding has some useful implications. It shows that each risk measure has a value and purpose which is unique to itself, with each reflecting risk emanating from different channels. The paper shows that large banks from one particular country appear to pose the greatest systemic threat to the financial system whereas, in the event of a systemic crisis emerging, banks located in a different country appear to be most exposed.

By testing the relationship between forward (lead) levels of the two systemic risk measures and balance sheet data, several variables are shown to be correlated. Institution size is the most important factor, in that it is consistently correlated with systemic risk, regardless of the systemic risk measure employed. Confirming the theories of Brunnermeier et al. (2009) and Goodhart et al. (2009) maturity mismatch, expected default frequency and, to a lesser extent, market-to-book ratios, are statistically significantly correlated. Particularly in the case of MES, which captures an institution's sensitivity to financial system shocks, leverage and non-interest-income-to-interest-income ratios are statistically significant. Non-performing loans are also significant, but have only a small marginal impact on systemic risk scores.

More factors are correlated with systemic risk as measured by ΔCoVaR than is the case with MES. Thus, these results confirm the main findings of Adrian and Brunnermeier (2016) and demonstrate that ΔCoVaR can provide useful information to macroprudential policy makers and supervisors. Because of this, any policy introduction / calibration intervention is likely to have a long-term beneficial impact. Evidence that time-varying ΔCoVaR demonstrates early warning characteristics is also provided given that many institutions' ΔCoVaR values as seen to deteriorate (i.e. systemic risk is increasing) in the months leading up to the financial crisis. By contrast, MES appears to be much more of a coincident indicator of systemic stress.

In addition, concerns about how informative systemic risk measures are relative to traditional risk measures such as value-at-risk and Market Beta appear somewhat overstated. Over time these measures may be correlated with their SRM "cousins" but in cross sections there appears to be very little relationship between them. Given that one of the primary raison d'etre of a systemic risk measure is to gauge the potential negative externalities associated with institution distress, understanding the change in the systemic threat posed by that institution is more important (to those charged with securing the stability of the financial system) than the change in idiosyncratic risk measured by a tool such as value-at-risk, even if both happen to be strongly correlated over time.

Regardless of which systemic risk measure is used it would appear that the systemic threat posed by European banks to the financial system (and vice versa) is currently (i.e. as of mid-2015) low, with pre-financial crisis risk levels presently observed. Of course, banking crises may originate outside of Europe and subsequently impact European institutions, an eventuality which this paper does not empirically examine. Also, banking crises can escalate rapidly and systemic risk levels increase as Figures 3 to 5 show, so there is little room for complacency. Systemic risk measures are found to be sensitive to the choice of financial system, frequency of measurement and selection of state variables, to such an extent that the ostensibly low systemic risk levels reported here may be misleading. Until there is a universally-recognised standard underpinning the definition of these systemic risk measures their usefulness will be limited to a guidance role for now.

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