Identifying systemically important banks in Sweden – what do quantitative indicators tell us?

ELIAS BENGTSSON, ULF HOLMBERG AND KRISTIAN JÖNSSON*

All authors work at the Financial Stability Department of the Riksbank. Elias Bengtsson is an associate professor in finance, Ulf Holmberg holds a PhD in economics and Kristian Jönsson is an associate professor in economics.

Identifying systemic institutions has developed into a key policy priority in the wake of the global financial crisis. The Basel Committee on Banking Supervision has developed global standards on systemically important banks (SIBs), and the implementation of those standards in Europe requires national authorities to identify banks that are systemically important on a domestic level based on quantitative and qualitative analysis. However, developing such a methodology is a difficult task that involves several difficult choices. One such choice concerns whether, which and how quantitative indicators can be used to identify SIBs.

This paper seeks to offer some guidance on designing a methodology for identifying SIBs in a Swedish setting. Based on a quantitative approach, the paper investigates to what extent are various indicators of systemic importance complementing or substituting each other; the extent to which various simple and advanced indicators produce consistent indications of systemic importance; and whether opting for simple indicators in designing a methodology for identifying SIBs would suffice; or whether such a choice lead to a disregard of vital aspects of systemic importance.

We find that the four largest Swedish banks' systemic importance increased before the financial crisis and that systemic risk increased sharply during the crisis in 2008-2009. We also find that systemic importance remained elevated during the sovereign debt crisis while falling as tension eased in 2012. Thus, the findings show that banks' systemic importance based on the indicators varies substantially over time. However, the various indicators yield rather different results on the ranking of systemically important banks and seem to be complementary to a large extent. The policy implication is to simultaneously consider a multitude of indicators when seeking to identify and differentiate between systemically important banks. Regulatory authorities thus face a daunting task in balancing the trade-offs between simplicity, transparency and predictability on the one hand, and a more advanced approach that may better capture systemic risk, but with complexity and opaqueness as a side-effect, on the other hand.

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IDENTIFYING SYSTEMICALLY IMPORTANT BANKS – A KEY OBJECTIVE

Identifying systemic institutions has developed into a key priority in the wake of the global financial crisis. This since the failure of a systemically important institution may disrupt both the financial system and economic activity. The disruptions to financial stability that became evident when seemingly non-systemic institutions failed was a stark reminder of the need for an ex ante view of which financial institutions may be or become systemic under certain circumstances. Likewise, the bail outs of institutions designated as systemic have led to large public expenses, socialized losses and arguably distorted market discipline for a considerable time to come.

In 2011, G20 mandated the global standard setter on banking regulation – the Basel Committee of Banking Supervision (BCBS) – to develop a framework to guide national authorities to address the policy problems associated with systemically important banks.[1] The following year, BCBS issued a range of principles for dealing with domestic systemically important banks (D-SIBs).[2] According to these principles, national authorities should establish a methodology for identifying systemic banks in a domestic context, and undertake regular assessments of the degree to which they are systemically important (principles 1 and 6).[3] In a European context, the implementation of the global standard into community law (the so-called CRD IV Directive) requires national authorities to identify banks that are systemically important on a domestic level based on quantitative and qualitative analysis.[4]

In Sweden, authorities have not formally designated any financial institution as systemically important to date. Nor have they announced any formalized methodology of identifying systemic institutions. However, in various policy statements and in the regulatory debate, the four largest Swedish banking groups are often implicitly or explicitly regarded as systemically important.[5] When the Ministry of Finance, the Riksbank and the supervisory authority announced their intention to make the four largest banking holding companies subject to higher capital requirements than other banks, the authorities pointed to four circumstances that motivate stricter rules: A large banking sector in comparison with the domestic economy; significant cross-border operations that make resolution

1 See G20 (2011).

2 For the full set of principles, see BCBS (2012).

3 BCBS´s framework for D-SIBs is considerably less prescriptive than its framework for global systemically important banks. National authorities seeking compliance with BCBS standards are thus given more flexibility in designing a framework for identifying D-SIBs.

4 Capital Requirements Directive IV Art. 124 a-c. It is also noteworthy that certain European countries–such as Switzerland, the UK and Denmark–already have implemented such methodologies.

5 See, for instance, the various statements issued by the Ministry of Finance, the supervisory authority and the Riksbank when the higher capital adequacy requirements for the four major Swedish banking groups were announced (Finansinspektionen 2011; Sveriges Riksbank 2011a; 2011b etc.). In these announcements, it is explicitly recognized that the higher capital adequacy does include the supplement for systemic importance developed by the Basel Committee and the Financial Stability Board.

cumbersome; a highly concentrated banking system where the financial services provided by an individual bank cannot be easily substituted; and extensive reliance on short term funding, particularly in foreign currencies. Taken together, the authorities argued that these circumstances imply significant social costs in the case of one or more of the large Swedish banks run into difficulties.[6] In other words, these circumstances contribute to financial institutions' systemic importance.

CAN QUANTITATIVE INDICATORS OFFER GUIDANCE?

Adopting such a purely judgment-based methodology to identify systemically important banks (SIBs) may be attractive in that it offers the authority responsible for finance stability a large degree of flexibility to designate any banks as systemically important. It also reduced the risk of relying on indicators that fail to capture the complex concept of systemic risk. However, in the absence of quantitative indicators, the methodology may be prone to criticism of being subjective, arbitrary and unpredictable.

These shortcomings could to some extent be circumvented. Constructing simple indicators of systemic importance on the basis of the four above circumstances (i.e. a large banking sector, significant cross-border operations, a highly concentrated banking system and extensive reliance on short term funding) is a relatively straightforward task. The indicators would use accounting data to serve as proxies for systemic risk, such as the size of banks or concentration in important markets (e.g. lending or deposit taking). Such simple indicators are attractive in that they are intuitive, relatively easy to implement in practical regulatory policy, and easily explained to legislative bodies and the public.[7] It however raises the question whether such a methodology would encompass sufficient indicators to capture the multifaceted and complex concept of systemic importance – simple accounting-based indicators are intrinsically backward-looking and perhaps provide a deceptive and too simplistic view of the extent to which banks contributes to systemic risk.[8]

One option would be to complement the methodology with some indicators that seek to identify SIBs by using an approach that is more forward looking in that they are based on market data, and more clearly related to economic theory. Such advanced indicators of systemic importance are attracting considerable interest from both the academic community and from policy makers. In principle, these advanced indicators measure systemic risk by relying on elaborate statistical techniques and econometric calculations typically using valuations from financial markets. Thus, these techniques are designed to harvest the markets perception of the financial institutions' systemic importance. While these approaches produce indicators that may be more forward looking and founded in economic theory, they are also fraught with a number of weaknesses that make them

6 See for instance Sveriges Riksbank (2011b) for a discussion.

7 For these reasons or others, a number of policy bodies and regulatory authorities have advocated or deployed simpler indicators as a basis for identifying systemically important financial institutions (c.f. IMF, FSB and BIS (2009); Swiss Commission of Experts (2010); Committee on Systemically Important Financial Institutions in Denmark (2013) etc.).

8 For a discussion on the weaknesses of simple indicators, see Bisias et al. (2012).

problematic and/or cumbersome from a policy perspective. Most notably, valuations on financial markets may not be available for all financial institutions. Also, measures of systemic importance derived from valuations on financial markets may be distorted by e.g. explicit and implicit state guaranties. If market actors anticipate future bail outs of systemically important banks, this will be reflected in the pricing of those banks' assets (e.g. stock prices) and debt which in turn will affect the market based measures of systemic importance.

Depending on the set-up of the methodology to identify (and regulate) SIBs, market participants may be provided incentives to influence indicators through market manipulation.[9] Taken together, systemic importance is a multifaceted concept that in fact may be hard to estimate using quantitative approaches.

DESIGNING A METHODOLOGY FOR IDENTIFYING SIBS INVOLVE TRADE-OFFS

Policy makers thus face a difficult choice in designing a methodology for identifying SIBs. In essence, policy makers should strive for a methodology that encompasses sufficient indicators to capture the multifaceted and complex concept of systemic importance, while at the same time retaining simplicity. This raises important questions regarding the indicators of systemic importance:

- To what extent are various indicators of systemic importance complementing or substituting each other?
- To what extent do the various simple and advanced indicators produce consistent indications of systemic importance? Are those indicators stable over time and under changing conditions?
- Would opting for simple indicators in designing a methodology for identifying SIBs suffice? Or does such a choice lead to a risk of disregard of vital aspects of systemic importance?

This paper seeks to offer some guidance on designing a methodology for identifying SIBs in a Swedish setting. Following an overview of the rapidly evolving literature on advanced indicators of systemic importance (section 2), the paper accounts for the methodological approach, including the choice of indicators and the data used to calculate them (section 3). This is followed by empirically investigating the explanatory power of the simple indicators on the advanced indicators in a Swedish setting (section 4). The paper concludes by discussing the policy implications of the results (section 5).

The findings are that banks' systemic importance, based on the indicators, are highly correlated and tends to vary substantially over time. In addition, the various indicators yield different results on the ranking of systemically important banks, even though each indicator provides a rather constant ranking over time. Thus, the various indicators of systemic importance seem to be complementary to a large extent. The policy implication is

9 For a comprehensive discussion on the pros and cons of market based indicators, see IMF, BIS and FSB (2009).

to simultaneously consider a multitude of indicators when seeking to identify and possibly differentiate between systemically important banks. These policy implications could be considered in the future implementation of BCBS's D-SIB standards and the CRD IV in Sweden.[10]

Identifying systemically important banks and measuring systemic risk

The concept of systemically important banks is well founded in the academic literature on financial stability. Yet, following a number of bank failures with wide-ranging repercussions on the financial system and a number of bank rescues (some of which still plague public finances in many countries) during the global financial crisis, interest in the topic has soared. And the body of research devoted to measuring systemic importance and identifying systemically important banks has expanded rapidly.

While it is widely recognized that systemic importance derives from systemic risk, agreement on how to measure systemic risk is still remote.[11] After all, systemic risk is a multifaceted phenomenon that may arise from different sources and spread through various channels.[12] Consequently, a disparate range of measures have been proposed by the academia. To provide an overview of the research field, we adopt the common way of distinguishing between methods that measures the vunerability of separate banks and measures that estimates the vunrerability of the financial system to measure systemic risk (cf. Drehmann and Tarashev 2011).

METHODS THAT ASSESS THE VULNERABILITY OF INDIVIDUAL BANKS

One possibility is to measure the vulnerability of particular financial institutions to system-wide distress. This means that the impact of a systemic shock on individual banks is calculated. Examples include the Marginal Expected Shortfall (MES) of Acharya et al. (2010), which measures a financial institution's expected loss when the market falls below some predefined threshold over a given time horizon. Another example is the Systemic Risk Measures (SRISK) of Brownless and Engle (2011) and Engle, Jondeau and Rockinger (2012). SRISK-measures estimates the expected capital shortfall of a financial institution, conditional on a crisis occurring.

Adrian and Brunnermeier (2011) proposes a conditional Value-at-Risk[13] (VaR) approach (ΔCoVaR), that can be used to calculate the VaR of banks under the condition that the financial system is under stress (ΔCoVaR-Bank). Segoviano and Goodhart (2009) introduce

10 For instance, the European Capital Requirements Directive (CRD IV) articles 124a provides guidance but also offers leeway to national authorities in identifying SIBs and making them subject to additional capital requirements.

11 In fact, a universally accepted definition of systemic risk is also missing (c.f. Bisias et al. 2012).

12 For a discussion, see Bisias et al. 2012.

13 The Value-at-Risk (VaR) is a threshold value expressing the minimum loss for a given time period with some small probability. Thus, a 5 per cent VaR of 100 million SEK for a period of five days expresses that there is a 5 per cent probability that losses will exceed 100 million SEK during a period of five days.

a measure that captures dependencies among banks' probabilities of default through linear and non-linear dependencies between banks in the banking system as a whole. A final example is Brunnermeier, Gorton and Krishnamurthy (2011), who unlike the above methods include the liquidity position of banks to assess impact on system-wide net liquidity in systemic risk. Taken together, these methods are useful for understanding the vulnerability of a particular financial institution to systemic shocks, but they do not capture how distress in that institution impacts on the system.

METHODS FOR ASSESSING THE VULNERABILITY OF THE FINANCIAL SYSTEM

Besides the methods described above, there exist methods that capture how important a particular financial institution is for the system as a whole. Conceptually, such methods calculate the impact on the financial system contingent on a particular financial institution in distress. For example, Acharya, Engle and Richardson's (2012) capital shortfall approach measures the maximum monetary loss of the system that can be expected to occur with some small probability, conditional on a particular financial institution being in a distressed state. Billio et al (2012) proposes a Granger causality test to examine whether the development of a bank's stock price may be useful in forecasting developments in another bank's share price. The existence of such a causality could be a sign that there is a connection between banks that can cause contagion. The more contagion a bank can cause, the more important the bank is.

There are also other approaches that look into how individual institutions contribute to system-wide stress through network effects (c.f. Upper 2011; Allen Babus 2009; Chan-Lau et al. 2009; Billio et al. 2010) or various forms of interconnectedness and joint probabilities of default (Segioviano and Goodhart 2009; Gieseke and Kim 2009; Fender and McGuire 2010; Lucas et al. 2013). The systemic contingent claim analysis of Gray and Jobst (2010, 2011) extends the traditional risk-adjusted balance sheet model to determine the magnitude of systemic risk as well as the contribution of individual institutions to systemic (solvency) risk. Jobst (2012) describes a method that measures systemic risk by modeling system wide liquidity. The CoVaR-measure of Adrian and Brunnermeier (2011) can also be used in order to measure the VaR of the financial system, conditional on a particular bank being in distress (ΔCoVaR-System). In addition, tools derived from multivariate extreme value theory can also be adopted into measures financial institutions' contribution to systemic risk (see Hartmann et al. 2006)

While the various approaches are complementary in measuring systemic risk, it is also noteworthy that several approaches can be calculated to encompass systemic risk both through the vulnerability of individual banks and the system as a whole (c.f. Segioviano and Goodhart 2009; Adrian and Brunnermeier 2011).

In the following section, we account for how a selection of the above indicators, and a number of other more simple indicators, were calculated for a number of Swedish banks. Thereafter, in Section 4, we empirically investigate the questions set out in the introductory section.

Methodology and data

To analyze whether there are any useful proxies for systemic importance, we calculate and compare a number of indicators for the four largest Swedish banks (Svenska Handelsbanken, Nordea, SEB and Swedbank). We adopt a terminology where we distinguish between simple and advanced indicators. Simple indicators are based on recent policy statements by regulatory authorities and the Riksbank, and cover a number of structural characteristics of the Swedish banks and financial markets (see Section 1). The advanced indicators stem from academic research (discussed in Section 2) and are based on more sophisticated statistical techniques, designed to summarize financial institutions systemic risk in a single measure.

Below, we discuss the rationale for our choice of indicators and how they relate to the concept of systemic risk (technical details on how they are calculated are provided in Annex A). Thereafter, we describe the econometrics used to determine whether and which of the simple indicators that can be considered useful proxies for systemic importance measured by the advanced indicators. Finally, we outline the data sources used and data characteristics.

SIMPLE INDICATORS

To identify a range of simple indictors, we draw upon a number of circumstances in the Swedish banking sector that Swedish authorities repeatedly have highlighted in discussions on systemic banks and the vulnerability of the Swedish banking system.[14] Below, we list these factors and the corresponding simple indicators developed to capture the risks the factors give rise to (for a more detailed description of the simple indicators, see Table 2 below). It is important to note that the relationship between simple indicators and systemic importance varies; indicators that relate to a large banking sector, significant cross-border operations and the concentration of the banking system signals increasing systemic importance. However, the indicators on reliance on short term funding are formulated so that they should have a negative relation to the measures of systemic importance that consider the vulnerability of individual banks. In other words, a bank should be less vulnerable to system-wide distress if it relies on domestic deposits or other stable sources of funding, or if it has larger liquidity reserves.

14 See, for instance, Sveriges Riksbank (2011); Finansinspektionen (2011) and Ministry of Finance (2008).

Table 1. Selection of simple indicators based on circumstances in the Swedish banking sector

BANKING SECTOR CIRCUMSTANCES	SIMPLE INDICATORS
A large banking sector in comparison with the domestic economy	Total assets
Significant cross-border operations that make resolution cumbersome	Total assets
A highly concentrated banking system where the financial services provided by an individual bank cannot be easily substituted	Domestic deposit taking Domestic lending* Market share – government bonds Market share – mortgage bonds Market share – futures and forwards Market share – foreign exchange
Extensive reliance on short tern funding, particularly in foreign currencies	Domestic deposit taking/equity (negative) Stressed liquidity reserve (negative)** Structural liquidity (negative)***

* We proxy domestic lending with company level lending to attain comparable time series.
** The Riksbank's measure of a bank's stressed liquidity reserve is used as a proxy for the Liquidity Coverage Ratio.
*** The Riksbank's measure of a bank's structural liquidity is used as a proxy for the Net Stable Funding Ratio.

It is noteworthy that the identified simple indicators correspond closely to those suggested by the conceptual framework developed by BCBS (2012) to identify D-SIBs.[15] Annex B outlines the developments in the simple indicators for the sample banks for the period 2005-2012.

ADVANCED INDICATORS

From the numerous advanced approaches to measure systemic importance of banks outlined in Section 2, we have used the following measures: the Marginal Expected Shortfall (MES) of Acharya et al. (2010), the Systemic Risk Measure (SRISK) of Brownless and Engle (2011) and Acharya, Engle and Richardson (2012), the Delta Conditional Value-at-Risk (ΔCoVaR) of Adrian and Brunnermeier (2011) and the Granger causality measure proposed by Billio (et al. 2012). The choice of these measures is based on their high impact on the academic and policy debate. Also they can all be estimated using public data. While all except the Granger causality measure are theoretically related (see Benoit et al. 2012 for a detailed discussion), these indicators measure somewhat different aspects of systemic risk.

As mentioned in Section 2, the *MES-measure* corresponds to a financial institution's expected loss when the market falls below some predefined threshold over a given time horizon.[16] The underlying notion is that that the institutions with the highest MES contribute the most to market declines. As such, banks with the highest MES are the greatest drivers of systemic risk. In the subsequent analysis, we calculate three different versions of the MES. The first version – MES 1 – defines the threshold (i.e. the distressed

15 According to BCBS's standard on D-SIBs, national authorities are recommended to take the following measures into consideration when identifying domestically systemic banks: (a) Size; (b) Interconnectedness; (c) Substitutability/financial institution infrastructure (including considerations related to the concentrated nature of the banking sector); and (d) Complexity (including the additional complexities from cross-border activity) (BCBS 2012).

16 For a more detailed description of the MES measure, see Annex A.

region) as a 2 percent market decline during one trading day. This holds true also in the second version – MES 2 – but this version uses the banks' beta to alleviate the results from stochastic movements. MES 3 is an alternative measure that acknowledges the clustering of volatility in market returns and seeks to adjust for the fact that volatility in banks' capital levels tend to be correlated and clustered under certain periods.[17]

The *SRISK-measure* estimates the expected capital shortfall of a financial institution, conditional on a crisis occurring.[18] In the SRISK measure, the intuition is that the financial institution with the largest capital shortfall will contribute the most to a crisis. Therefore it should be considered as the most systemically important. Just as for MES, we calculate three versions of SRISK. In the first version, SRISK 1, a crisis is defined as a situation where the market declines by at least forty per cent over a six-month period.[19] The SRISK 2 uses the banks' beta to alleviate the results from stochastic movements, just like its MES counterpart. This also applies to the SRISK 3, which acknowledges the clustering of volatility in market returns and adjusts for the fact that volatility in banks' capital levels tend to be correlated and clustered under certain periods.[20]

In the subsequent analysis, as was discussed, the third measure ΔCoVaR-*System* measures the contribution of a financial institution to systemic risk. It is calculated from the Conditional Value-at-Risk (CoVaR) which is analogous with the conventional Value-at-Risk (VaR). CoVaR-System measures the maximum monetary loss of the system that can be expected to occur with some small probability, conditional on a particular financial institution being in a distressed state. ΔCoVaR-System is simply the difference between the systems CoVaR when the financial institution is in its distressed state and when it is not.[21]

The CoVaR-System measure can be modified in order to measure the Value-at-Risk of financial institution, conditional on the system being in its distressed state (c.f. Adrian and Brunnermeier 2011). We denote this measure as ΔCoVaR-*Bank* and use it as a complement to the indicators discussed above.

The *Granger causality* test proposed by Billio et al. (2012) tests for pairwise causality between all the banks in a banking system, modeling the change in a bank's share price as a function of past changes in the bank's share price and past changes in another bank's share price. Granger causality is said to exist if previous changes to the other bank's share price is statistically significant in the model.[22] In this paper, all pairwise combinations of banks are examined in this way.

17 See Brownless and Engle (2012).
18 For a more detailed description of the SRISK measure, see Annex A.
19 The definition of a crisis is based on the insights of Acharya et al. (2010).
20 See Brownless and Engle (2012).
21 For a more detailed description of the ΔCoVaR measure, see Annex A.
22 For a more detailed description of the Granger causality measure, see Annex A.

THE SELECTION OF INDICATORS

On reflection, it is notable that the indicators selected for the subsequent analysis adopt a somewhat differing concept of systemic risk. As discussed in Section 2, measures of systemic risk can be distinguished in terms of whether they estimate the impact on the financial system should a particular financial entity fail, or whether they seek to measure the sensitivity of any particular financial entity to stress in the financial system.

The simple indicators that relate to size and market shares in deposit taking, lending and market shares in markets for certain important financial instruments represent the former category. The simple indicators on the funding profile of the banks (domestic deposit taking /equity; stressed liquidity reserve (negative); structural liquidity (negative)), on the other hand, rather relate to the sensitivity of the bank in question to financial system stress. Likewise, whereas ΔCoVaR-System, SRISK and Granger causality measures the impact of an individual bank failure on the financial system, MES and ΔCoVaR-Bank indicates the sensitivity of individual institutions to financial system stress. In this respect, the selected indicators complement each other and enable a fuller picture of how different indicators of systemic stress relate to each other in the Swedish setting.

DATA DESCRIPTION

To analyze the relationship between the simple and advanced indicators, we define the system as the Swedish financial market. The simple indicators are calculated on a quarterly basis and cover the period 2005Q2-2012Q3.[23] The advanced indicators are estimated using daily market data covering the period April 6 1999 to November 21 2012. For these indicators, the stock market index OMXS30 is used as a proxy for developments in the Swedish financial system. We relate the advanced indicators of systemic risk to the simple indicators by calculating moving averages over 30 trading days, while using the last trading day per quarter as our measurement point.

Table 2 below provides an overview of the simple and advanced indicators, their definition in terms of how they are calculated and their data sources.

Descriptive statistics for the daily return series used to calculate the advanced indicators is provided in Table 3 below. It shows that the four largest Swedish banks' returns are more volatile than the index. Also, their returns exhibit considerable kurtosis while the skewedness varies between banks. Thus, we choose to use the empirical distributions when calculating the advanced indicators and since the banks' minimum daily returns range between -20 and -10 per cent, it is possible that the use of the empirical distributions in order to calculate the ΔCoVaR-indicators will result in slightly different distress levels.

23 For the stressed liquidity reserve and for the banks structural liquidity, we use comparable pairs of data covering the period 2005Q4-2012Q2. For missing observations, we interpolated between quarters to achieve a balanced data panel.

Table 2. Overview of the simple indicators and the advanced indicators

SIMPLE INDICATORS	DEFINITION	DATA SOURCE
Total assets	Total group level balance sheet assets in relation to GDP	Statistics Sweden
Domestic deposit taking	Market share of Swedish retail, non-financial corporations and public sector deposit taking	Statistics Sweden
Lending	Share of total company level lending to retail, non-financial corporations and public sector entities	The Riksbank
Market share – government bonds	Market share in Swedish government bond market total turnover	The Riksbank/Selma
Market share – mortgage bonds	Market share in mortgage bond market total turnover	The Riksbank/Selma
Market share – futures and forwards	Market share in futures and forwards total turnover	The Riksbank/Selma
Market share – foreign exchange	Market share in Swedish foreign exchange market total turnover	The Riksbank/Selma
Domestic deposit taking/equity	Swedish retail, non-financial corporations and public sector deposit taking as a percentage of bank equity	The Riksbank/Statistics Sweden
Stressed liquidity reserve	Liquidity reserves in relation to a stressed cash outflow (for details see Sveriges Riksbank 2010)	Liquidatum/ The Riksbank
Structural liquidity	Stability of funding in relation to maturity of assets (for details see Sveriges Riksbank 2010)	Liquidatum/ The Riksbank
ADVANCED INDICATORS	DEFINITION	DATA SOURCE
MES	The expected shortfall of a bank given that the system moves into distress	The Riksbank/Bloomberg
SRISK	The amount of capital a bank is expected to need given a financial crisis	The Riksbank/Bloomberg
ΔCoVaR-System	The bank's contribution to the systems VaR given that the bank becomes distressed	The Riksbank/Bloomberg
ΔCoVaR-Bank	The system's contribution to the bank's VaR given that the system becomes distressed	The Riksbank/Bloomberg
Granger causality	The effect on bank's share price as a function of past changes in the bank's share price and past changes in another bank's share price	The Riksbank/Bloomberg

Table 3. Descriptive statistics of the daily return series used to calculate the advanced indicators

	MEAN	STD.DEV	MIN	MAX	SKEWNESS	KURTOSIS
OMXS30	0.0002	0.0164	-0.0817	0.1037	0.1918	3.0342
Handelsbanken	0.0006	0.0194	-0.1018	0.1421	0.5174	5.3174
Nordea	0.0005	0.0228	-0.1149	0.1609	0.5549	5.0396
SEB	0.0005	0.0267	-0.2000	0.2613	0.5500	9.6145
Swedbank	0.0005	0.0248	-0.1856	0.1894	0.1955	7.8460

Note. Based on daily market data covering the period April 6 1999 to November 21 2012.

In the following section, we account for the results of the analysis. We begin by outlining developments in the advanced indicators in 2005-2012. Thereafter, relations between the simple and advanced indicators are described and discussed.

Systemic importance of Swedish banks

DEVELOPMENTS IN SYSTEMIC IMPORTANCE OF SWEDISH BANKS

The rankings and developments in the advanced indicators between 2005 and 2012 for the sample of large Swedish banks are depicted in Figure 1 and Figure 2 below.[24] The following observations are notable:

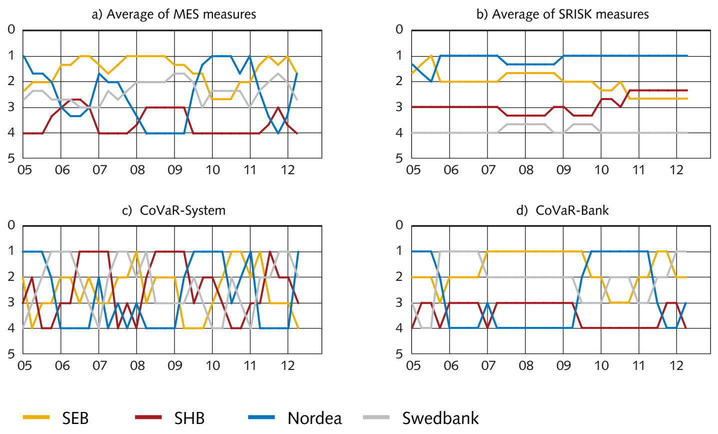
- The systemic importance of banks according to the advanced indicators varies considerably over time. It is notable that all advanced indicators but SRISK indicated that systemic risk increased in 2006 as the crisis approached. All indicators increase sharply as the crisis became fully fledged in 2008-2009. They increased again in 2011 as the Sovereign debt crisis took hold, and subsequently fell as tension eased in 2012. The increase in systemic risk during periods of market stress stems partly from our choice of estimation which effectively allows the banks' market risk to vary over time.[25] Thus, if the market perceives a bank more risky during time of distress, this will be reflected in the advanced indicators of systemic importance.
- The degree to which systemic importance differs between the individual banks is also noteworthy. The MES, ΔCoVaR-Bank and ΔCoVaR-System indicates that the systemic importance of the four banks is rather similar over the period. However, based on the SRISK indicators, Nordea becomes far more systemically important than its peers from 2008 and onwards. This deviation from the other banks' systemic importance may be attributed the rapid growth in Nordea's liabilities relative the other Swedish banks during the same time period.
- The advanced indicators tend to rank the banks in the sample rather differently. For example the SRISK-indicator ranks Nordea as far more systemically important than its peers, especially from 2008 and onwards. According to the MES and ΔCoVaR-Bank indicators, SEB is the most systemically important bank for the time period. However, according to the ΔCoVaR-System indicator, SEB frequently ranks as the least systemically important bank in the sample, even though the level of the difference between the banks is small. Handelsbanken ranks low according to all indicators but the ΔCoVaR-System. This could be interpreted as the bank being rather insensitive to systemic shocks, while the system tends to be dependent on the viability of the bank. In other words Handelsbanken tends to alleviate adverse market developments better than its Swedish peers, possibly due to the bank's decentralized decision making structure (see Holmberg et al. 2012).
- While the ranking of banks varies across the advanced indicators, each provides a rather constant ranking over time. MES, SRISK and ΔCoVaR-Bank maintains a stable ranking of the banks over time (with a limited number of exceptions). The ranking

24 See Figure B1 in Annex B for an outline of developments in the simple indicators for the sample banks 2005-2012.

25 See Annex A for details of the estimation techniques.

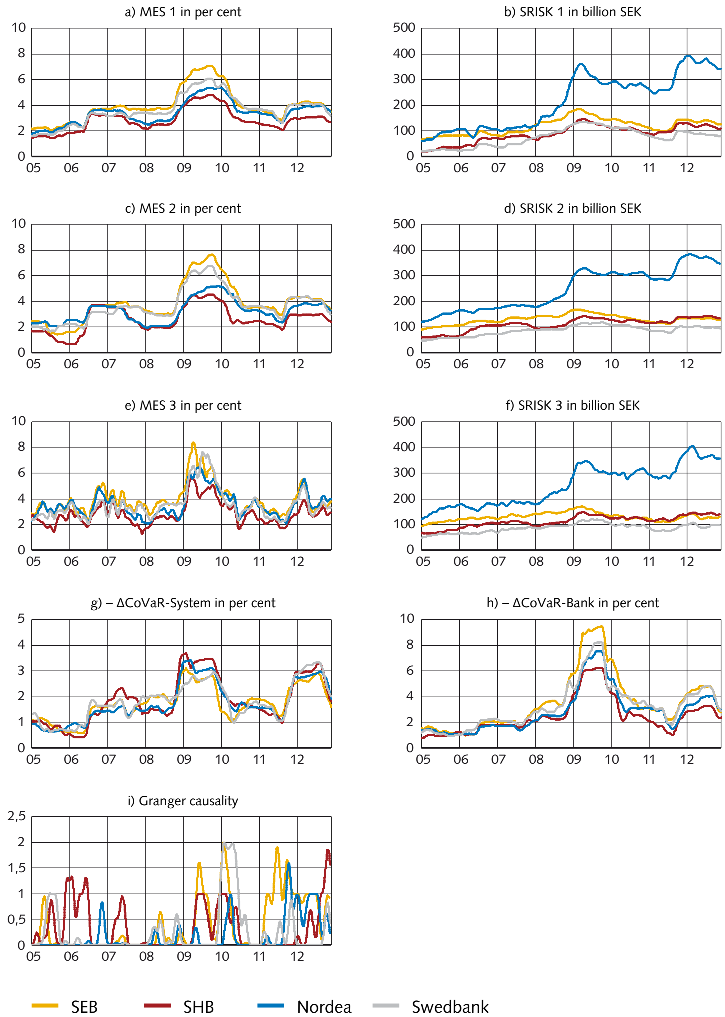
according to ΔCoVaR-System, on the other hand, varies considerably between 2005 and 2012. This is probably attributable to the small difference between banks in the estimated value of the ΔCoVaR-System indicator such that the rankings are within the error margins. The exception is the Granger measure. According to this indicator, each of the four banks is the most systemically important bank at at least one point in time between 2005-2012.

Figure 1. Ranked systemic importance of the advanced indicators



Note. The higher the ranking the larger the systemic risk.

Figure 2. Thirty day moving averages of the advanced indicators 2004-2012



Note. For illustrative purposes, the figures on ΔCoVaR-System and ΔCoVaR-Bank indicators show the negative outcome of the calculations.

RELATING THE SIMPLE INDICATORS TO THE ADVANCED INDICATORS

We begin studying the relationship between simple and advanced indicators by investigating their correlation. Table 4a below displays the pooled correlations between the indicators, were significant results are highlighted in bold. It shows that only total assets and deposit taking provides consistent signs of the correlation coefficient.[26] Total assets, market share in government, mortgage bonds and foreign exchange are all associated with a larger degree of systemic importance according most of the advanced indicators. The same applies to structural liquidity, even though the correlation between structural liquidity

26 We pair observations quarterly in order to get balanced panels. All results are based on standardized variables.

and most vulnurability measures relating to individual banks (MES and -ΔCoVaR-Bank) are non-significant. However, deposit taking is associated with lower systemic risk across all advanced indicators, which is consistent with expectations. For all other simple indicators, the correlation displays variation from positive to negative across the advanced indicators.

Table 4b displays the ranked correlations of the simple and advanced indicators. It is striking that several advanced indicators display significant ranked correlations with the simple indicators. This is particularly noteworthy for the different variations of MES and SRISK, which display significant correlation with between 5 and 7 of a total of 10 simple indicators. However, the only simple indicators with a consistent sign of the correlation coefficient across all advanced indicators are size, deposit taking, market share in mortgage bonds and stressed liquidity reserve. In the case of deposit taking, the sign is negative, which suggest that those banks that rely on deposit taking tend to be less systemically important. For all other simple indicators, the direction of correlation varies across the advanced indicators. However, market share in government bonds, futures and forwards and foreign exchange display a strong tendency of displaying a positive ranked correlation with most advanced indicators (all but -ΔCoVaR-System).

However, the ambiguity of the relationship between the advanced indicators and the simple indicator in Table 4 may be a consequence of the linear relationships of the simple correlation matrix being highly influenced by bank specific effects. As such, the simple correlations in table 4 may over- or underestimate the dependence between the advanced and simple indicators. Furthermore, since numerous of the simple indicators are highly correlated (see Annex B), we asses statistical significance through panel data regressions models with fixed effects for each pair of normalized variables.[27] The results from the paired panel data regression are displayed in table 5 below, were bold text indicates significance and grey text non-stationarity.[28]

27 Note that the paired panel data regressions may result in omitted variable bias. However, since we are interested in the direct relationship between the simple and advanced indicators, we ignore this issue in favor of more clearly interpretable results.

28 In general, there is a large discrepancy between the estimated within-group and between-group coefficients of determinations; suggesting that the pooled correlations in table 4 fit the data poorly.

Table 4a. Pooled correlations between the advanced and simple indicators

	MES 1	MES 2	MES 3	SRISK 1	SRISK 2	SRISK 3	-ΔCOVAR-SYSTEM	-ΔCOVAR-BANK	GRANGER
Total assets	0.07	0.12	0.12	0.97***	0.90***	0.98***	0.16*	0.11	0.05
Deposit taking	-0.16*	-0.18**	-0.14	-0.45***	-0.43***	-0.44***	-0.06	-0.16*	-0.24***
Lending	-0.13	-0.10	-0.02	0.84***	0.70***	0.85***	-0.02	-0.09	-0.06
Gov. bonds	0.16*	0.16*	0.16*	0.33***	0.35***	0.33***	-0.01	0.12	0.24***
Mortg. bonds	0.40***	0.40***	0.33***	0.05	0.13	0.04	-0.01	0.31***	0.08
Futures and forwards	0.08	0.13	0.10	-0.15*	-0.11	-0.15	-0.09	0.09	0.02
Foreign ex.	0.03	0.10	0.11	0.33***	0.32***	0.34***	-0.04	0.05	0.09
Deposit taking/equity	-0.07	-0.10	-0.13	-0.84***	-0.73***	-0.84***	-0.01	-0.08	-0.09
Stressed liquidity reserve	0.22**	0.19**	0.11	-0.11	-0,04	-0.13	0.10	0.13	0,06
Structural liquidity	0.13	0.09	-0,01	0.22**	0.21**	0.20**	0.09	0.05	0,17*

Significance codes: '***':1%, '**':5%, '*':10%. Significant results are highlighted in bold.

Table 4b. Pooled ranked correlations between the advanced and simple indicators

	MES 1	MES 2	MES 3	SRISK 1	SRISK 2	SRISK 3	-ΔCOVAR-SYSTEM	-ΔCOVAR-BANK	GRANGER
Total assets	0.13	0.19**	0.21**	0.97***	0.79***	0.97***	0.14	0.17*	0.08
Deposit taking	-0.14	-0.17*	-0.16*	-0.61***	-0.55***	-0.61***	-0.06	-0.15*	-0.26***
Lending	-0.32***	-0.33***	-0.19**	0.56***	0.28***	0.58***	-0.10	-0.29***	-0.13
Gov. bonds	0.20**	0.17*	0.17*	0.29***	0.30***	0.28***	-0.00	0.10	0.11
Mortg. bonds	0.31***	0.33***	0.28***	0.03	0.15	0.00	0.02	0.23**	0.06
Futures and forwards	0.04	0.08	0.08	0.06	0.07	0.07	-0.01	0.07	0.06
Foreign ex.	0.07	0.12	0.13	0.48***	0.38***	0.49***	-0.03	0.05	0.10
Deposit taking/equity	-0.14	-0.15*	-0.18*	-0.80***	-0.66***	-0.80***	0.03	-0.11	-0.16***
Stressed liquidity reserve	0.24**	0.24**	0.14	0.08	0.13	0.06	0.15	0.20**	0.10
Structural liquidity	0.21**	0.16	0.04	0.35***	0.30***	0.31***	-0.03	0.09	0.22**

Significance codes: '***':1%, '**':5%, '*':10%. Significant results are highlighted in bold.

The first conclusion is that size matters. Not only does an increase in the banks' total assets increase systemic risk (according to MES, SRISK and -ΔCoVaR-System indicators); an increase in total assets also tends to increase the banks' sensitivity to systemic shocks (-ΔCoVaR-Bank). All these results are significant. The results also show that deposit taking/equity has a significant and negative relation to systemic risk according to all advanced indicators but -ΔCoVaR-System. The same applies to market share of deposit taking for all advanced indicators but MES 3, where significance is missing. For other simple indicators, evidence is more mixed. Lending, market shares in government bonds, mortgage bonds and foreign exchange, as well as stressed liquidity reserve, display significant relationships for between two and five advanced indicators. The only simple indicators merely demonstrating one significant relationship is structural liquidity (for the Granger causality indicator).

Approaching the results with the advanced indicators as a basis, one observation is that six of the ten simple indicators have a significant correlation with the Granger causality indicator when controlling for fixed bank effects. However, the direction of the relationship varies and three simple indicators have a positive relationship to both SRISK indicators (total assets; market share in government and mortgage bonds; structural liquidity) and three a negative one (deposit taking; market share in futures and forwards; deposit taking/equity). This result can be explained for deposit taking/equity since a higher rate of deposit funding should make a bank less prone to failure. However, a higher market share in deposit taking should make a bank more systemically important. Hence, the negative relationship to advanced indicators is somewhat harder to explain. For the other advanced indicators, between two and four simple indicators have significant relationships, albeit with different signs for the correlation (both positive and negative). The exceptions are the SRISK indicators with between six and seven significant relationships with simple indicators. However, since these results may be spurious due to non-stationarity (see further below) they should be interpreted with caution.

Another observation is that the structural liquidity indicator has only one significant relationship with the advanced indicators while the stressed liquidity reserve has none. The structural liquidity indicator has a significant positive relationship with the Granger causality indicator, a measure reflecting the interconnectedness of banks. This result is somewhat hard to interpret since one would expect a bank with higher structural liquidity to be less prone to transmit stress through the financial system. However, since the banks' structural liquidity reserves and their total assets are correlated and historically move in tandem (see Annex B), this result may stem from omitted variable bias. Indeed, by controlling for size the relationship turns negative and loses its significance.[29]

ADJUSTING THE RELATIONSHIP BETWEEN SIMPLE AND ADVANCED INDICATORS FOR TRENDS

A closer comparison of the developments in simple indicators and the advanced indicators reveals that some paired panel data regressions produce non-stationary residuals thus making the results unreliable (see Granger and Newbold 1974). It is evident from the results in Table 5 denoted in grey text that this merely concerns the various SRISK measures. For these indicators we thus proceed with paired panel data regressions on the first differences. From Table 6, it is observable that the only simple indicator that remains significantly related to the SRISK measures is our measure of size (total assets).

29 When controlling for size, as measured by total group level balance sheet assets in relation to GDP, the relationship between the Granger causality indicator and the stressed liquidity reserve is -0,12 and non-significant.

Table 5. Results from the paired panel data regressions with fixed effects. The over-all (left) and the within-group (right) coefficients of determinations are in the parenthesis

	MES 1	MES 2	MES 3	SRISK 1	SRISK 2	SRISK 3	-ΔCOVAR-SYSTEM	-ΔCOVAR-BANK	GRANGER
Total assets	**0.88*** (0.25/0.13)**	**1.03*** (0.30/0.18)**	**0.61*** (0.17/0.06)**	**1.40*** (0.98/0.94)**	1.77*** (0.94/0.89)	**1.33*** (0.98/0.92)**	**1.27*** (0.23/0.23)**	**1.15*** (0.24/0.20)**	**0.59** (0.06/0.05)**
Deposit taking	**-0.43*** (0.19/0.06)**	**-0.37** (0.18/0.05)**	-0.11 (0.12/0.00)	-0.34*** (0.73/0.11)	-0.43*** (0.55/0.11)	-0.28*** (0.75/0.08)	**-0.31* (0.03/0.03)**	**-0.42** (0.10/0.05)**	**-0.63*** (0.13/0.12)**
Lending	-0.55 (0.15/0.01)	-0.19 (0.14/0.00)	0.04 (0.11/0.00)	**2.69*** (0.80/0.34)**	**2.94*** (0.61/0.24)**	**2.69*** (0.82/0.36)**	0.05 (0.00/0.00)	-0.15 (0.05/0.00)	-0.54 (0.02/0.00)
Gov. bonds	0.09 (0.15/0.01)	0.07 (0.15/0.00)	0.05 (0.12/0.00)	0.08 (0.71/0.02)	**0.13* (0.51/0.03)**	0.07 (0.73/0.02)	0.02 (0.00/0.00)	0.08 (0.06/0.01)	**0.30*** (0.09/0.07)**
Mortg. bonds	**0.30** (0.19/0.05)**	**0.27** (0.18/0.04)**	0.19 (0.13/0.02)	**0.14** (0.71/0.04)**	**0.21** (0.52/0.04)**	**0.13* (0.73/0.03)**	0.05 (0.01/0.00)	**0.31** (0.10/0.05)**	0.13 (0.02/0.01)
Futures and forwards	0.08 (0.14/0.00)	0.18 (0.15/0.01)	0.09 (0.12/0.00)	-0.07 (0.70/0.00)	-0.05 (0.49/0.00)	-0.06 (0.72/0.00)	**-0.37* (0.03/0.03)**	0.12 (0.05/0.00)	**-0.36* (0.04/0.03)**
Foreign ex.	-0.20 (0.15/0.01)	-0.09 (0.15/0.00)	-0.16 (0.12/0.01)	0.09 (0.70/0.01)	0.13 (0.50/0.01)	0.08 (0.72/0.01)	-0.02 (0.00/0.00)	-0.06 (0.05/0.00)	0.10 (0.01/0.00)
Deposit taking/ equity	**-1.12*** (0.24/0.12)**	**-1.12*** (0.25/0.12)**	**-0.68** (0.15/0.04)**	**-0.47*** (0.72/0.06)**	**-0.77*** (0.54/0.09)**	**-0.40** (0.74/0.05)**	-0.48 (0.02/0.02)	**-1.31*** (0.19/0.15)**	**-1.46*** (0.18/0.17)**
Stressed liq. reserve	0.12 (0.17/0.01)	0.06 (0.17/0.00)	-0.04 (0.11/0.00)	**0.26*** (0.76/0.13)**	**0.30*** (0.56/0.09)**	**0.24*** (0.77/0.11)**	0.23 (0.03/0.03)	0.03 (0.06/0.00)	-0.03 (0.02/0.00)
Structural liquidity	0.09 (0.17/0.01)	0.03 (0.17/0.00)	-0.07 (0.11/0.00)	0.07 (0.73/0.02)	0.07 (0.52/0.01)	0.04 (0.74/0.01)	0.11 (0.02/0.01)	0.03 (0.06/0.00)	**0.17* (0.04/0.03)**

Significance codes: '***':1%, '**':5%, '*':10%. Significant results are highlighted in bold. Non-stationary results in grey.
Note. For comparison the regressions are based on first order differences on normalized data.

Table 6. Results from the paired panel data regressions with fixed effects on first differences. The over-all (left) and the within-group (right) coefficients of determinations are in the parenthesis

	SRISK 1	SRISK 2	SRISK 3
Total assets	**1.13*** (0.72/0.70)**	**1.66*** (0.66/0.65)**	**0.88*** (0.37/0.35)**
Deposit taking	0.01 (0.04/0.00)	0.02 (0.02/0.00)	-0.00 (0.03/0.00)
Lending	0.49 (0.06/0.02)	0.71 (0.04/0.01)	0.51 (0.05/0.01)
Gov. bonds	0.00 (0.04/0.00)	0.00 (0.02/0.00)	-0.01 (0.03/0.00)
Mortg. bonds	-0.00 (0.04/0.00)	0.01 (0.02/0.00)	0.00 (0.03/0.00)
Futures and forwards	-0.00 (0.04/0.00)	0.02 (0.02/0.00)	-0.05 (0.05/0.01)
Foreign ex.	0.03 (0.05/0.01)	0.04 (0.03/0.00)	-0.03 (0.04/0.00)
Deposit taking/ equity	0.08 (0.05/0.01)	0.03 (0.02/0.00)	0.01 (0.03/0.00)
Stressed liquidity reserve	0.02 (0.05/0.00)	0.03 (0.03/0.00)	-0.01 (0.04/0.00)
Structural liquidity	0.06 (0.06/0.01)	-0.01 (0.03/0.00)	0.06 (0.04/0.01)

Significance codes: '***':1%, '**':5%, '*':10%. Significant results are highlighted in bold text.
Note. For comparison the regressions are based on first order differences on normalized data.

Discussion and policy implications

This paper has outlined a range of simple and advanced indicators for the Swedish banking system; compared whether these indicators yield similar assessments of systemic importance; and investigated to what extent these indicators produce consistent indications of systemic importance over time. The results show that the systemic importance attributed to each individual bank varies substantially across indicators. But while the various advanced indicators tend to rank the banks differently in terms of systemic importance, for most indicators the ranking tends to be relatively constant over time as depicted in Figure 1. This holds true regardless of whether the indicator is based on a concept of systemic importance that measures the impact of an individual bank failure on the financial system or the sensitivity of individual institutions to financial system stress. In addition, the indicators show a build-up of systemic risk during the years predating the financial crisis and a sharp rise in individual banks' systemic importance after the collapse of Lehman Brothers. The banks' systemic importance have remained at an elevated level and experienced an increase during the most intensive period of the European sovereign debt crisis. The banks' systemic importance tends to display similar patterns over time, with one exception. Based on the SRISK indicators, Nordea becomes far more systemically important than its peers from 2008 and onwards. A similar pattern is observable for the simple indicator that measures the size of individual banks (se annex B).

The findings of this paper indicate that:

- It is possible to quantitatively assess the banks in terms of their systemic risk. Thus, quantitative indicators can be used in combination with thresholds or simple scoring to distinguish systemic banks from non-systemic banks, or rank banks according to their systemic importance.
- The relatively large variation over time in terms of systemic importance points to the importance of avoiding a static approach to identifying systemic banks. Any approach to identifying systemic banks and differentiating between them, should use a dynamic approach, and carefully consider the appropriate frequency of the identification process.
- Identifying systemic banks merely using a single indicator could lead to premature or wrong conclusions. The results show that systemic importance is highly depending on the definitions and criteria used in the calculation of each indicator. Thus, any approach to identify systemic banks should take a multitude of indicators into account. A mixture of simple and advanced indicators would probably yield more useful results than relying merely on either of these types of indicators. However, taking too many indicators into account increases complexity. Besides, a formalized identification process does imply difficult choices in terms of what indicators to include, as well as deciding on the relative weight the different indicators should be assigned.

- The results also points to the difficulty of using a purely quantitative approach in identifying and differentiating between systemic banks. Given the large variation between banks and over time, using a (single or combined) scoring to identify systemic banks implies a lot of challenges. Not only because alternative important indicators may be omitted; also because it may yield a false sense of actually being able to correctly measure systemic risk. In practice, systemic risk is a complex and multifaceted concept, affected not only by bank-specific conditions but also by various feedback-loops between risks in various parts of the financial system and policy measures. Taken together this calls for a combination of quantitative and qualitative analysis (as proposed in the CRD IV) and a possible avenue for future research could be the development of methods that combine the informational content in each indicator into an index of systemic importance.

Taken together, these results suggest that regulatory authorities responible for Financial stability face a daunting task in balancing the trade-offs between simplicity, transparency and predictability on one hand, and a more advanced approach that may better capture systemic risk, but with complexity and opaqueness as a side-effect on the other hand. Despite the difficult choices involved in developing a methodology for identifying systemically important banks, policy makers should not delay the process since such work could contribute to reducing systemic risk. The choice between doing something to cumber the externalities that stem from systemically important banks, even though it may suffer from shortcomings, and doing nothing because of the complexities involved should be an easy one.

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Annex

A. ADVANCED INDICATORS – TECHNICAL DESCRIPTION

Annex A discusses the advance indicators used in the analysis and presents the details regarding the estimation procedures. Since all advanced indicators are based on market data, we let r_t^i denote the daily stock return of bank i at time t.

The ΔCoVaR measures

The Value-at-Risk (VaR) of a bank's firm level risk is defined as the maximum potential loss that will not be exceeded over a given time horizon for some small probability (see Jorion 2007 for a survey) such that the daily VaR for the return r_t^i satisfies:

$$Pr\{r_t^i \leq VaR_{t,\alpha}^i\} = \alpha \tag{A.1}$$

That is, with some small probability α, the bank experiences a negative daily return of less than $VaR_{t,\alpha}^i$. Following Adrian and Brunnermeier (2011) we denote $CoVaR_{t,\alpha}^{j|r^i \leq VaR_{t,\alpha}^i}$ as the VaR of bank j conditional on bank i being at its VaR level:

$$CoVaR_{t,\alpha}^{j|r^i \leq VaR_{t,\alpha}^i} = VaR_{t,\alpha}^j | r_t^i \leq VaR_{t,\alpha}^i \tag{A.2}$$

Given the above, define $\Delta CoVaR$ as:

$$\Delta CoVaR_{t,\alpha}^{j|i} = CoVaR_{t,\alpha}^{j|r^i \leq VaR_{t,\alpha}^i} - CoVaR_{t,\alpha}^{j|r^i \leq median} \tag{A.3}$$

The expression in equation (A.3) quantifies bank i's contribution to bank j's VaR when bank i moves from its 'normal' median level to its distressed VaR level. By replacing bank j with the financial system, equation (A.3) expresses systemic risk as measured by the indicator $\Delta CoVaR$-System. By replacing i with the financial system, equation (A.3) expresses systemic risk as measured by the indicator $\Delta CoVaR$-Bank.

In the analysis, the $\Delta CoVaR$ indicators are estimated using quintile regression and as a first step; the following relation is estimated:

$$r_t^i = \beta_{j,0} + \beta_{j,1}^{\alpha} r_t^i, \tag{A.4}$$

which gives the linear relationship between bank i and bank j's stock returns at the quintile given by α. Given equation (A.4), $\beta_{j,1}^{\alpha}$ can be used in order to calculate bank j's $CoVaR$:

$$CoVaR_{t,\alpha}^{j|i} = \beta_{j,0} + \beta_{j,1}^{\alpha} VaR_{\alpha}^i. \tag{A.5}$$

By combining equation (A.5) with equation (A.3), $\Delta CoVaR$ can be calculated. In the analysis, $\Delta CoVaR$-System is calculated by replacing j with the financial system and $\Delta CoVaR$-Bank is calculated by replacing i with the financial system. Both $\Delta CoVaR$ indicators are calculated using a 250 trading day rolling window such a bank's market risk is allowed to vary over time.

Marginal Expected Shortfall and SRISK

The Marginal Expected Shortfall (MES) is derived from Expected Shortfall (ES) which is given by the expected loss given that the VaR is exceeded:

$$-ES^{i}_{t,\alpha} = E_t\left[r^{i}_{t} \mid r^{i}_{t} \leq VaR^{i}_{t,\alpha}\right]. \tag{A.6}$$

where E_t corresponds to the expectation conditioned on all available information up to time t. The MES utilizes this concept and measures the expected shortfall of bank i conditioned on the financial system j being in distress:

$$-MES^{i}_{t,C} = E_t\left[r^{i}_{t} \mid r^{j}_{t} \leq C\right], \tag{A.7}$$

where C is some extreme negative quintile defining a market in distress. In the analysis, C is -2 per cent such that the MES is the one day expected loss given that market returns are less than -2 per cent

The $SRISK$ measure of Brownless and Engle (2011) and Acharya, Engle and Richardson (2012) seek to quantify the Capital Shortfall (CS) of a bank, conditioned on the financial system moving into a distressed state. Given the book value of debt (D)[30], the CS of a bank is given by:

$$\begin{aligned} CS^{i}_{t} &= k \times D^{i}_{t} - (1-k) \times Eq^{i}_{t+\tau} \times E_t\left[r^{i}_{t} \mid r^{j}_{t} \leq C^*\right] \\ &= k \times D^{i}_{t} - (1-k) \times Eq^{i}_{t+\tau} \times LRMES^{i}_{t}, \end{aligned} \tag{A.8}$$

where Eq is the financial firms market valued equity, C^* is the long run distressed state defining the Long Run Marginal Expected Shortfall ($LRMES$) and where k is a required percentage minimum of equity.[31] In the analysis, we follow Acharya, Engle and Richardson (2012) and let C^* be a forty per cent market decline over a six-month period such that the $LRMES$ can be approximated with:

$$LRMES^{i}_{t} \approx 1 - exp(-18 \times MES^{i}_{t,C}), \tag{A.9}$$

30 In the analysis we use linear interpolations between quarters to get daily measurements of the book value of debt.

31 In the analysis, k is assumed to be 8 per cent.

where MES is calculated in accordance with equation (A.7). $SRISK$ is then defined as:

$$SRISK_t^i = max(CS_t^i, 0). \tag{A.10}$$

In the analysis, we use different measures of the MES and $SRISK$. The differences between the measures spring from how a bank's MES is calculated and in the first measure, MES 1, we use a static approach and calculate a bank's MES by the means of equation (A.7) while utilizing the empirical distributions of r_t^i and r_t^j. For the second measure, MES 2, we smooth the estimates by utilizing that MES can be calculated from the banks' betas:

$$MES_t^i 2 = -\beta_t^i \times E_t\left[r_t^i | r_t^j \leq C\right], \tag{A.11}$$

where $\beta_t^i = COV(r_t^i, r_t^j)/VAR(r_t^j)$ and where r_t^j represents return of the market (system). However, since financial returns tend to be clustered (see Engle, 1982) the third and final measure, MES 3, model returns as multivariate GARCH processes with dynamic conditional correlation as discussed in Engle and Sheppard (2001). Thus, the estimation procedure for MES 3 is close to the econometrics in Brownlees and Engle (2010) and Engle et al. (2012). Finally, the three MES measures are used together with equation (A.9) and (A.10) in order to retrieve their corresponding $SRISK$ measures. All MES indicators are calculated using a 250 trading day rolling window such a bank's market risk is allowed to vary over time.

The Granger Causality Measure

The systemic risk measure introduced by Billio et al (2012) use Granger causality tests to examine whether the development of a bank's stock price may be useful in forecasting developments in another bank's stock price. The argument used is that the existence of Granger causality could be a sign that there is connection between banks that can cause contagion. The more contagion a bank can cause, the more important the bank is.

Granger causality is a statistical notion of causality based on the ability of one variable to forecast the value of another variable. In terms of the notion above, r_t^i is said to Granger cause r_t^j if past values of r_t^i contain information that helps predict r_t^j above and beyond the information contained in r_t^j alone (Billio et al., 2012). In the analysis, we test for Granger causality by first specifying a bivariate $VAR(p)$ model, i.e. a vector auto regressive model of order p:

$$\begin{bmatrix} r_t^i \\ r_t^j \end{bmatrix} = \begin{matrix} \beta_0^i \\ \beta_0^j \end{matrix} + \sum_{k=1}^{p} \begin{bmatrix} \beta_{1,k}^i & \beta_{2,k}^i \\ \beta_{1,k}^j & \beta_{2,k}^j \end{bmatrix} \times \begin{bmatrix} r_{t-k}^i \\ r_{t-k}^j \end{bmatrix} + \begin{bmatrix} e_t^i \\ e_t^j \end{bmatrix}, \tag{A.12}$$

where e_t^i and e_t^j are random error terms subject to the usual assumptions. Within the $VAR(p)$ framework, bank *j* is sad to Granger cause bank *i*'s stock return if at least one of the parameters $\beta_{2,k}^i$ for $k = 1, ..., p$ are statistically significant different from zero. In such a case, previous values of bank i's stock return have predictive power in determining the future value of bank j's stock return and Granger causality is said to exist. By the same argument, if at least one of the parameters $\beta_{2,k}^{i}$ for $k = 1, \ldots, p$ are statistically significant different from zero, bank i is sad to Granger cause bank j's stock return.

In the analysis, we determine the order of lags in the $VAR(p)$ by the means of Schwartz information criteria, restricting the order to a maximum of $p = 20$. All Granger causality tests are based on the 5 per cent significance level and the total number of statistically significant Granger causality tests is used as an indicator of systemic importance.

B. SIMPLE INDICATORS

Table B1. Correlations between the simple indicators

	TOTAL ASSETS	DEPOSIT TAKING	LENDING	GOV. BONDS	MORTG. BONDS	FUTURES AND FORWARDS	FOREIGN EX.	DEPOSIT TAKING/ EQUITY	STRESSED LIQUIDITY RESERVE
Deposit taking	-0.41***								
Lending	0.93***	-0.22**							
Gov. bonds	0.34***	-0.29***	0.24***						
Mortg. bonds	-0.00	-0.35***	-0.19**	0.39***					
Futures and forwards	-0.20**	-0.57***	-0.36***	0.12	0.30***				
Foreign ex.	0.33***	-0.75***	0.16*	0.34***	0.30***	0.67***			
Deposit taking/ equity	-0.90***	0.56***	-0.87***	-0.40***	-0.12	0.09	-0.46***		
Stressed liquidity reserve	-0.22**	-0.35***	-0.44***	0.01	0.29***	0.48***	0.37***	0.18*	
Structural liquidity	0.20**	-0.23**	0.11	-0.00	0.10	-0.22**	0.15	-0.30***	0.51***

Significance codes: '***':1%, '**':5%, '*':10%.
Note. For comparison the correlations are based on normalized data.

Figure B1. Developments in the simple indicators 2005-2012