The Role of Macroprudential Indicators in Monitoring Systemic Risk and Setting Policy

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Abstract

The financial crisis demonstrated the damaging effects that the build-up of systemic risk in the financial system can have. However, due to the complex and constantly evolving nature of the modern financial system, monitoring systemic risk is not a straightforward task. As part of its systemic risk monitoring framework, the Central Bank maintains over 80 macroprudential indicators which reflect the multifaceted nature of systemic risk. The effectiveness of these indicators can be further enhanced by establishing indicator values associated with elevated risk levels and through the use of visualisation methods, such as heatmaps. While these indicators are used throughout the policy making process, they are not mechanically tied to policy decisions and policy maker judgement also plays a central role. This paper discusses the Central Bank's approach to the use of macroprudential indicators.

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1. Introduction

The financial crisis demonstrated the damaging effects that the build-up of systemic risk in the financial system can have and has led to the development of a range of macroprudential policies to mitigate this type of risk. Systemic risk is defined by the Central Bank of Ireland as the risk of a disruption to the provision of financial services, caused by an impairment of all or parts of the financial system, with serious negative consequences for the real economy (CBI, 2014). Systemic risk can take many forms and has both time and structural dimensions. Due to the dynamic nature of the financial system, it is also likely to evolve over time. This contrasts with monetary policy which generally addresses one or two specific objectives, which are directly measureable and defined. As a result, the monitoring of systemic risk requires a multifaceted approach and a wide range of indicators.

As Ireland's macroprudential authority the Central Bank is responsible for monitoring systemic risk in the Irish financial system and implementing policies to limit its impact on both the financial system and the real economy.² The Central Bank employs a broad suite of analytical tools and methodological approaches to monitor systemic risk. These include monitoring macroprudential indicators, conducting on-going conjunctural analysis, which is published on a bi-annual basis in the Macro-Financial Review, and employing advanced quantitative techniques.³

In this Article we focus on the role of macroprudential indicators. The Central Bank has constructed over 80 indicators required to monitor systemic risk. These are centrally stored in a database and are mapped onto types of risk through its structure, which categorises indicators in line with the Central Bank's intermediate objectives of macroprudential policy. These objectives reflect the Central Bank's initial focus on the banking sector, given its prominent role in the intermediation process in Ireland.⁴ The intermediate objectives are as follows;

- 1. to mitigate and prevent excessive credit growth and leverage;
- to prevent excessive maturity mismatch and market illiquidity;
- to limit direct and indirect exposure concentrations and;
- to reduce the potential for systemically important banks to adopt destabilising strategies and to mitigate the impact of such actions.

The Article builds upon previous publications by the Central Bank outlining the overall framework for macroprudential policy (CBI, 2014) and available instruments of macroprudential policy (Grace, Hallissey and Woods, 2015). It is intended to further expand the information and knowledge in the public domain regarding the macroprudential policy framework, by providing an overview of the indicators of systemic risk used by the Bank and their role in assessing risk and implementing policies. Section 2 outlines the role of indicators in setting macroprudential policy, alongside the additional role of expert judgement. Section 3 discusses several key indicators in the context of intermediate objectives of macroprudential policy, the existing literature and their behaviour in the Irish and European financial systems. Section 4 gives an overview of approaches to linking indicator values with risk levels and to synthesising information contained in the indicators. Section 5 concludes.

- 2 The Central Bank is Ireland's national macroprudential authority for the purposes of the European Systemic Risk Board's (ESRB) 2011 Recommendation and is the designated national authority responsible for certain macroprudential powers in the Capital Requirements Regulation and Directive ('CRR/CRD IV'). For further information see the Central Bank's framework for macroprudential policy (CBI, 2014).
- 3 Examples of the latter include macro-financial modelling (Clancy and Merola, 2014; Lozej, Onorante and Rannenberg, 2017), micro-level loan loss forecasting models (Gaffney et al., 2014; Gaffney, Kelly and McCann, 2014; Kelly and O'Malley, 2014), price misalignment models for the real estate sector (Kennedy, O'Brien and Woods, 2016; Kennedy and McQuinn, 2012) and network models of interconnectedness between banks (Hallissey, 2016; Downey, Lyons and O'Malley, 2017).
- 4 The intermediate objectives are laid out in the Central Bank's framework for macroprudential policy (CBI, 2014) and are influenced by those set out by the European Systemic Risk Board (ESRB) in ESRB Recommendation 2013/1.

2. The role of indicators in policy setting

2.1 Macroprudential policy cycle

The process for setting macroprudential policy is a continuous cycle with four key stages, as shown in Figure 1. The first stage is systemic risk assessment, followed by instrument selection and calibration. Policies must then be implemented, followed by evaluation and monitoring. After this fourth stage the process begins again with systemic risk assessment.⁵ Macroprudential indicators are key to each of these four stages.

During the first stage of the policy cycle, effective and well-constructed indicators are required to identify existing or emerging risks. While all policy relies on good data, access to a broad range of high quality indicators is particularly important in macroprudential policy due to the multifaceted nature of systemic risk in a modern financial system. The indicator database's structure is particularly useful during the second stage. Indicators are categorised by intermediate objectives, which in turn can be mapped onto different macroprudential risks and instruments (see Grace, Hallissey and Woods (2015) and ESRB (2014) for further discussion). As a result, discussion regarding instrument selection can be more focussed, although policy maker judgement will also play a central role (this is addressed in further depth in Section 2.2).

During the third stage, policy implementation, availability of high quality indicators is crucial to both timing and communication. As many macroprudential instruments aim to prevent the build-up of systemic risk, implementation at a point when imbalances have already accumulated may severely limit effectiveness (Drehmann and Juselius, 2013; Caruana, 2010). Clear communication of policy goals should further enhance the effectiveness of

Figure 1: Macroprudential policy cycle



Source: CBI (2014)

measures through a signalling effect and by providing market participants and the general public with insight into the Central Bank's decision making process (Caruana, 2010; BIS, 2016).⁶

The final stage of the macroprudential policy process is policy evaluation. The Central Bank reviews all of its macroprudential policies on a regular basis to determine whether changing risk levels may require re-calibration. The indicators are a key resource in this regard and allow for continuous monitoring of relevant risks. This is particularly important for cyclical instruments where risks are likely to fluctuate and the necessity to "release" an instrument may arise very rapidly.⁷

2.2 Role of judgement

Despite the central importance of indicators throughout the macroprudential policy cycle their application is not mechanical and judgement also plays a crucial role. The need for policy maker discretion in setting macroprudential policy arises from both the nature of systemic risk and current limitations in its measurement and detection.

6 Examples of this communication approach include the Central Bank's announcements regarding the Countercyclical Capital Buffer (CCyB) (see CBI, 2016).

⁵ These stages are discussed in further detail in the Central Bank's framework for macroprudential policy (CBI, 2014).

⁷ For example, the CCyB requires banks to build up capital buffers during periods where aggregate lending growth in an economy is accelerating. The buffer can then be released during periods of systemic stress, allowing banks to maintain credit supply to a greater extent than would otherwise be the case. While the build-up phase often takes place over a number of years, reductions in credit supply can materialize very quickly and as such it is crucial that policy makers have access to timely measures of systemic stress (Drehmann, Borio and Tsatsaronis, 2011).

Firstly, due to the dynamic nature of the financial system it is likely that future systemic risk will arise in ways not captured by existing measurements. This could take the form of new risks arising from financial innovation or the financial system's responses to macroprudential policies. Due to the evolution of the financial system in terms of contracts, institutions, technology and operations, previously observed systemic risks may also present themselves in new ways. As a result, establishing a mechanical link between a fixed set of indicators and policy setting based on historical experience could lull policy makers into a false sense of security (Agur and Sharma, 2013).

Second, mechanical interpretation of individual indicators faces difficulty in tying specific indicator values to systemic risk levels. As financial crises are infrequent events it is difficult to construct statistically sound associations between indicator values and risk levels (see Section 4.1). Furthermore, given the complexity of modern economies, the effects of systemic risk are often non-linear and assuming that the future path of systemic risk can be quantitatively inferred from a given indicator is unrealistic. For example, the impact of a particular form of systemic risk may be state dependent and its ultimate effect on the real economy may differ dramatically across different economic environments (Chiu and Hacioglu Hoke, 2016; Haldane, 2012).

Finally, due to the multifaceted nature of systemic risk, there is not yet a single model or single metric by which systemic risk can be measured. Transmission mechanisms of macroprudential tools are also not yet fully understood.⁸ In this context it is useful to again compare macroprudential policy with monetary policy. Inflation targeting monetary policy has a far longer track record than is available for most macroprudential instruments, allowing for the development of an extensive toolkit and literature. Despite this, much of the existing literature concludes that monetary policy still remains both "art" and "science" and that judgement should continue to play a role in decision making (Blinder, 1998; Svensson, 2003; Blanchard, 2006; Mishkin, 2007). Similarly, and in most cases to a greater extent, the use of both quantitative assessment of macroprudential indicators and policy maker judgement is recommended in setting macroprudential policy.⁹

3. Intermediate objectives of macroprudential policy

To provide an overview of the macroprudential indicators used by the Central Bank, this section examines a number of key indicators and the ways in which they relate to each of the intermediate objectives. It should be noted that this discussion focuses on a selection of indicators and is in no way reflective of the entire range of indicators monitored by the Central Bank.

3.1 Intermediate objective 1

The first intermediate objective of macroprudential policy is to prevent excessive credit growth and leverage. The role of excess credit growth in causing financial crises has been well documented in the academic literature (Minsky, 1972; Barajas, Dell'Ariccia and Levchenko, 2007; Claessens, Kose and Terrones, 2008; Mendoza and Terrones, 2012). Its effects can be further amplified by excess leverage, which both facilitates credit growth and makes individuals and institutions less resilient to its reversal. A wide range of indicators have been constructed to monitor these risks, such as measures of aggregate and sectoral credit dynamics, bank leverage, real estate pricebased indicators, measures of real estate price

8 The development of comprehensive systemic risk models, composite indicators, calibration tools and impact assessment methods are all areas of intensive research in both academia and policy making institutions with notable recent contributions in these areas including Gambacorta and Karmakar (2016), Schuler, Hiebert and Peltonen (2015) and Baptista et al. (2016).

⁹ A concrete example of this approach can be found in CCyB setting. Both the Basel Committee on Banking Supervision (BCBS) (BCBS, 2010) and the EU's Capital Requirements Directive IV (CRD IV) recommend the use of a "buffer guide" whereby the value of a country's credit-to-GDP gap is mapped directly onto a potential CCyB rate. This mapped value, combined with the judgement of policy makers, is used to set the ultimate rate. Such an approach has been implemented across EU member states, including Ireland. Credit-to-GDP gap values, buffer guide values, rationale for policy setting and resulting CCyB rates can be found on the ESRB website.

misalignment, aggregate loan to value (LTV) and loan to income (LTI) ratios and measures of investment in real estate.

Following the financial crisis, the use of the credit aggregates as indicators of systemic risk has gained traction in both the academic literature and in policy making. In particular, the deviation of the credit-to-GDP ratio from its long term trend (referred to as the credit-to-GDP "gap") is put forward by Drehmann, Borio and Tsatsaronis (2011) as the preferred indicator of a build-up of cyclical systemic risk and is recommended by both the BCBS (BCBS, 2010) and the ESRB (ESRB, 2014b) as a core indicator in CCyB setting. The buffer guide (see footnote 9) also puts forward lower and upper thresholds, for the introduction of a positive CCyB and the use of a maximum CCyB of 2.5 per cent respectively, which are taken into consideration in the interpretation of these indicators.

However, the credit-to-GDP gap is not without its limitations. For example, the gap is calculated as deviation from long term trend, which in turn is calculated using a purely statistical technique.¹⁰ As a result the trend is not economically founded and will not account for structural changes to the economy which could alter equilibrium or sustainable credit levels (Czech National Bank, 2014; Buncic and Melecky, 2014). A number of macroprudential authorities have also found that prolonged periods of excess credit expansion or contraction can feed through to the trend calculation leading to over or underestimations of sustainable credit levels (Bank of England, 2015). These issues again highlight the importance of judgement in policy setting and have led to the development of a number of alternate versions of the measure by European authorities (Pekanov and Dierick, 2016).

In an Irish context the indicator faces further complications due to difficulties arising from both aggregate credit and GDP measurements. In the case of the former, large intra-group positions held by multinational corporations (MNC) resident in Ireland result in inflated aggregate credit measurements which may not reflect developments in the domestic economy (Creedon and O'Brien, 2016). Similarly, the influence of MNCs on headline Irish GDP figures has led to much debate as to whether or not the statistic represents a meaningful measure of domestic economic activity. This issue has become more pronounced over recent years due to corporate restructuring and methodological changes to GDP calculation (see Walsh, 2016).

To reflect this a number of credit-to-GDP gap measures are constructed. The first is the standard credit-to-GDP gap, constructed in line with ESRB Recommendation 2014/1, which reflects all credit in the Irish economy and uses a standard GDP measure. The second, referred to as the national specific credit-to-GDP gap, uses a credit aggregate which has been adjusted to remove the effect of Ireland's MNC sector and a standard GDP measure (for further discussion of this indicator see Creedon and O'Brien (2016)). The third is a credit to underlying domestic demand gap. This uses the national specific credit aggregate and a measure of domestic demand excluding investment in aircraft and intangible assets such as intellectual property.

As shown in Figure 2 all variations on this indicator rose substantially in the years leading up to the financial crisis, with both non-standard measures passing the lower threshold for CCyB setting in 1998 and reaching the upper threshold by between 1999 and 2003. The impact of changes to the 2015 national accounts data from mid-2016, which included substantial changes to both aggregate credit and GDP measures, resulted in a temporary but dramatic spike in the standard measure. This was primarily driven by the immediate impact of the change on aggregate credit combined with a more gradual impact to GDP, which is measured as a four quarter rolling sum.

In addition to these credit stock measures, a number of credit flow measures have been proposed by the literature. For example, Schularick and Taylor (2009) find credit growth to be a strong predictor of financial crises. As such year on year aggregate growth is calculated for each credit measure.

¹⁰ The trend level of the credit-to-GDP ratio is calculated using a recursive Hodrick-Prescott (HP) filter. This decomposes a time series into trend and cyclical components, dependent on a variable smoothing parameter. In this case a smoothing parameter of 400,000 is prescribed. A recursive, or one-sided, filter means only information available at each point in time is used for the calculation of the trend











Source: QFA and CSO.

Given the interaction between credit dynamics, leverage and real estate prices, real estate indicators form another important component of the Objective 1 indicators. These include direct measures of real estate prices, simple ratios aiming to capture price misalignment and the output of a number of advanced models aiming to do the same. A common ratio examined in this context is the price-to-rent ratio, where a high value implies prices may be in excess of fundamental returns on property investment,

thus suggesting the asset is overvalued. A more advanced approach to estimating overvaluation is laid out in Kennedy, O'Brien and Woods (2016). The authors use a number of reduced form models, based on developments in supply and demand factors such as income and housing supply, to estimate a time series for sustainable house prices.

As shown in Figure 3, all of these indicators rose dramatically over the years preceding the







Source: CSO.



Source: IPD.

Source: Central Bank calculations.

financial crisis and began falling between late 2006 and 2008. While price growth shows marked increases over the past two years, price levels and misalignment measures do not yet point to overvaluation in either residential or commercial markets.

3.2 Intermediate objective 2

The second intermediate objective of macroprudential policy is to mitigate and prevent excessive maturity mismatch and market illiquidity. This objective targets systemic risk arising from financial institutions relying excessively on short-term and unstable funding. Unstable sources include funding provided "wholesale" by other financial institutions, capital markets or sourced abroad and contrast with more stable funding from retail deposits. An increased reliance on unstable sources of funding can increase banks' vulnerabilities to system-wide runs, particularly when it is used to fund lending at long maturities. Risks arising from this type of activity often move in tandem with those covered by Objective 1 as nondeposit funding facilitates the rapid expansion of balance sheets (Hahm et al., 2013). A range of indicators have been constructed to capture these risks, including bank funding ratios, aggregate measures of bank maturity structures, liquid asset ratios, asset encumbrance ratios and market liquidity indicators.

The non-core funding ratio (NCFR) aims to capture risk arising from reliance on wholesale funding, using the ratio of funding sourced through security issuance to funding through deposits. The indicator features prominently in the literature on financial crisis early warning indicators where it is found to be a particularly effective leading indicator (Hahm et al., 2013). As shown in Figure 4 the behaviour of this indicator for domestic Irish banks mirrors that of the credit-to-GDP gap in the years leading up to the financial crisis.¹¹ This reflects the increased reliance of Irish banks on non-deposit funding to increase lending. In recent years the behaviour is also similar across the two indicators and they



Source: Money and Banking Statistics.

show how post-crisis deleveraging has been accompanied by a return to a more deposit funded model.

Risks associated with reliance on wholesale funding often build-up slowly and materialise rapidly. Banks which have become reliant on short term wholesale funding can suddenly face significant liquidity and funding challenges following increased risk aversion in wholesale funding markets. This realisation is captured by the difference between the rate at which European banks lend to one another (the Euro Interbank Offered Rate (EURIBOR)) and the overnight interest rate swap rate (Overnight Indexed Swap (OIS)) over the same period. This indicator spiked dramatically following the bankruptcy of Lehman Brothers and during the European sovereign debt crisis. This was driven by increased credit risk in the banking system leading to wholesale lenders requiring higher compensation for short term unsecured lending. In addition to providing a useful measure of banks' wholesale funding costs this indicator is available on a daily basis, making it a preferred option to indicators which are released at a lower frequency or with a lag.

¹¹ Domestic Irish banks refers to institutions included in the Domestic Market Group category used in the Central Bank's Money and Banking statistics; a comprehensive list of these institutions is available <u>here</u> on the Central Bank website. It should also be noted that these statistics are calculated on a residency basis, meaning that data are compiled on a locational basis so, for example, branches of foreign authorised entities located in Ireland are included in aggregate statistics and branches of Irish authorised entities located outside of Ireland are not. For a detailed explanation of residency based statistics and how this differs from the supervisory approach see O'Brien and Reen (2012).







Source: SNL.

Note: European average reflects average value for banks included in EBA stress test.

However, not all banks will be equally affected by negative funding shocks. For example, banks with a higher share of liquid and unencumbered assets on their balance sheet will be better able to manage such scenarios. The Liquidity Coverage Ratio (LCR), put forward by the Bank of International Settlements (BIS), aims to directly measure banks' ability to withstand market stress. It is constructed using the ratio of High Quality Liquid Assets (HQLA) to total cash outflows over a 30 day market stress scenario.¹² Under Basel III requirements this measure should not fall below 100 except during periods of financial stress, where banks may draw on their stock of HQLA (BCBS, 2013). Figure 6 shows the unweighted average LCR across Irish headquartered retail banks alongside the European average for comparative purposes.13 While the LCR of Irish banks are all in excess of the BIS requirement, they do lag behind their European counterparts.

3.3 Intermediate objective 3

The third objective of macroprudential policy is to limit direct and indirect exposure concentration. As the financial sector's exposures become more concentrated, risks related to these exposures may begin to pose systemic threat to the financial system. For example, if the banking system is heavily involved in funding a given sector, the risk of a downturn in that sector may become a systemic risk for the financial system. Realisation of this type of risk will often take the form of contagion, where negative developments in one sector spread through the wider financial system. Exposure concentration is seen as "direct" when financial institutions' balance sheets are directly and excessively exposed to a common risk. However, exposures can also be "indirect", as fragility in one part of the financial sector may lead to fire sales and reduce the prices of assets held by other institutions (ESRB, 2014).

While objectives one and two focus primarily on cyclical systemic risk, objectives three and four focus more on the cross-sectional, or structural, dimension of systemic risk. Structural systemic risks make the financial system more vulnerable to negative shocks and may interact with cyclical systemic risks by propagating or amplifying cyclical shocks. In most cases structural risks, and as an extension indicators used to measure them, are more slow-moving than cyclical risks.

¹² BIS defines HQLA as cash or unencumbered assets which can be converted into cash at little or no loss (BCBS, 2013)

¹³ This data is compiled on a supervisory basis and as such focuses on developments in the individual credit institutions or banking groups on a consolidated basis, taking into account all operations regardless of whether they are undertaken by offices located in Ireland. For a detailed explanation of supervisory based statistics and how this differs from the residency approach see O'Brien and Reen (2012).



Source: Central Bank of Ireland.

Furthermore, while there is an extensive literature on cyclical forms of systemic risk, such as credit and real estate bubbles, many of the risks in this category have been less studied and data sources tend to have shorter time series.

However, a wide range of more recent datasets are available. In compiling the indicators, a range of these sources have been drawn upon to examine concentration in banks' new lending and outstanding loans, concentration in bank security holdings to sectors, countries and individual counterparties, the magnitude of concentrated exposures relative to institutions' capital base, the magnitude of exposures between Irish banks and the distributions of total assets and leverage ratios across Irish authorised banks. Many of these measures are constructed at both institution and system-wide levels.

For example, high level regulatory returns can be used to assess concentration in sectoral exposures of Irish financial institutions in terms of total outstanding exposures and new lending. As can be seen in Figure 7, Irish retail banks are heavily exposed to the real estate sector, particularly in terms of household mortgage finance.¹⁴ While the concentration of new lending in household mortgage finance has decreased since 2010, it remains the largest single component of domestic bank new lending.

Since the financial crisis, a number of more granular data sources have also become available to the Central Bank, such as the large exposures dataset. This is collected by the Central Bank in its supervisory capacity and provides extensive exposure-level information on all large exposures held by Irish authorised banks.¹⁵ Hallissey (2016) uses this dataset to map exposures across the Irish financial system and the dataset is also extensively drawn up to monitor risk arising from exposure concentration. For example, total large exposures relative to an institution's capital base can be used to monitor the overall concentration of its exposures or exposures held by the system as a whole.

¹⁴ This classification of Irish retail banks is in line with the classification used in the Central Bank's Macro-Financial Review. This data is compiled on a supervisory basis and as such focuses on developments in the individual credit institutions or banking groups on a consolidated basis, taking into account all operations regardless of whether they are undertaken by offices located in Ireland. For a detailed explanation of supervisory based statistics and how this differs from the residency approach see O'Brien and Reen (2012).

¹⁵ A large exposure is defined as an exposure that is 10 per cent or more of a bank's eligible capital base and each bank authorised in Ireland must report these on a quarterly basis. Banks whose parent institution is authorised in Ireland (Irish headquartered banks) also report any exposures which are greater than €300 million. These exposures consist largely of loans but also include derivatives, guarantees and debt or equity holdings (Hallissey, 2016).

Figure 8 shows the evolution of this measure for Irish retail banks, where the indicator shows substantial but decreasing exposure concentration. The magnitude of this exposure is primarily driven by institutions' large sovereign bond holdings and by substantial parent company exposures (see Figure 10 for a full sectoral breakdown). It should also be noted that "eligible capital", which consists of an institution's tier one capital and a limited share of its tier two capital (see European Commission, 2016), is a fairly narrow capital measure which, as the measure's denominator, will further increase its value. The large exposures dataset also provides exposure values net of collateralisation and exemptions, where exemptions include sovereign bond holdings and exposures with certain type of parent company guarantees (Hallissey, 2016). These values are much smaller, ranging between 58 and 42 per cent over the period shown.

Figure 8 also highlights concentration within the banks' large exposures, as the ten largest exposures make up between 75 and 64 per cent of the total value over the course of the period shown. As a result, details of these exposures are also monitored including degree of collateralisation, total size and counterparty name, sector and country. Throughout the period shown these ten largest exposures are almost entirely made up of Irish sovereign bond holdings and exposures to parent companies. Their decreasing size, alongside rising eligible capital levels, drive the aggregate indicator's downward trend over the period.

Counterparty information is also used to assess concentration in exposures to specific counterparties, sectors and countries. Figure 9 provides a geographic breakdown of large exposures for the first quarter of 2014 and the final quarter of 2015. The charts show a strong but decreasing home bias among large exposures, along with substantial exposure to the UK.

Figure 10 provides a sectoral breakdown for the same two periods where government and credit institutions dominate; this is in line with



Source: Central Bank of Ireland.

the sectoral breakdown of the banks' ten largest exposures discussed above. Furthermore, the similarity in sectoral exposures across the two periods reflects the slow-moving nature of structural risks.

3.4 Intermediate objective 4

The fourth intermediate objective is to reduce the potential for systemically important banks to adopt destabilising strategies and to mitigate the impact of such actions. The financial crisis demonstrated that in many cases the cost of failure of systemically important, or too-big-to-fail (TBTF), institutions for the rest of the financial system and the real economy is high enough to result in government intervention (Siegert and Willison, 2015). While this may be an optimal solution on a case by case basis it also creates a moral hazard problem, whereby institutions who believe they will be bailed out in the case of bankruptcy have less incentive to prevent their bankruptcy from occurring. This may result in increased risk taking by systemically important



Source: Central Bank of Ireland.



Source: Central Bank of Ireland.

institutions, which both increases the likelihood of their failure and overall risk taking in the financial system (Afonso, Santos and Traina, 2014).

A range of indicators have been constructed which both assess incentives for systemically important banks to adopt destabilising strategies and the impact this could have on the real economy. These include indicators covering the size of individual institutions relative to GDP, the size of the system as a whole relative to GDP, measures of concentration across a number of key markets, measures of interconnectedness between Irish banks and the wider financial system, each other and the Irish state, measures of lending and funding concentration, measures of bank and system complexity, and measures of cross border activities.

While systemically important banks are often the largest banks in a financial system there are a number of attributes which, in addition to size, contribute to systemic importance. For example, if financial agents, such as borrowers or depositors, can substitute one institution for another without substantial market disruption, this could limit the impact on the system of an institution's failure. A number of measures of market share concentration are constructed and these are summarised in Figure 11. This chart shows the market share held by the three largest institutions in the markets for Irish private sector deposits, private sector loans, household loans and NFC loans. In all cases the three largest institutions command most of the market share, suggesting the failure of one would cause large scale disruption to the system and the real economy.

The Central Bank has also used a wide range of datasets and methodologies to conduct analysis of interconnectedness in the Irish financial system. The failure of an institution to which others are highly exposed can have a detrimental effect on the entire system; Brunnermeier et al. (2009) refer to this phenomenon as "too interconnected to fail". In addition to transmitting shocks, a high degree of interconnectedness can also contribute to the complexity of the financial system and increase the cost of allowing individual institutions to fail. In a complex or opaque financial system, where it is difficult to understand how and to what extent institutions are exposed to one another, the failure of one institution may give rise to adverse selection effects as investors are unable to distinguish between institutions which are and are not exposed to related losses. During the financial crisis this resulted in the freezing up of the interbank markets and forced asset sales (Claessens et al., 2010).

Examples include Downey, Lyons and O'Malley (2017) who use data from TARGET2-IE, Ireland's component of the Eurosystem's large value payment system (TARGET2). The authors examine connections between Irish banks arising from payment transactions, both customer and interbank. By mapping these two separate networks at a specific point in time, they find that interbank payment flows were mainly between a relatively small number of Irish banks and with a select number of international banks. They also find that three banks have many connections with each other and with other banks in the Irish customer network, while many banks in this network have very few connections. The authors draw upon literature from network analysis to construct a number of indicators identifying banks which are most important in the Irish interbank and customer payment networks. Their work also proposes a way of monitoring Irish payments data from a financial stability viewpoint and why this is important.

Hallissey (2016), on the other hand, uses large exposures data to map interbank exposures of all Irish authorised banks. This is shown in Figure 12 where circles (nodes) represent banks, lines connecting them represent credit exposures and circle size represents the sum of all exposures to that bank. The results of this analysis highlight that the network of bilateral interbank credit exposures held by Irish authorised banks is relatively sparse. There are a just a few key hubs in this network, all of which had been identified as systemically important at a global level (Global Systemically Important Institutions) at the time

16 It should be noted that this network shows only asset exposures held by Irish authorised institutions and as such does not provide a full picture of interconnectedness for the Irish banking system.





of writing.¹⁶ The large exposures dataset is also used to monitor interconnectedness between Irish retail banks at a granular level.

Of course size is also a key determinant of an institution's systemic importance and as such a number of indicators focussing on financial institutions' size have been constructed. Moreover, there is a direct link between the size of an institution, or the size of the financial system as a whole, and the impact the materialisation of TBTF risk will have on the real economy. Figure 13 shows the size of Ireland's domestic banking sector relative to Irish GDP where the rapid expansion of the financial sector, even relative to the size of the rapidly growing Irish economy, prior to the financial crisis is clear. Following the financial crisis substantial deleveraging has taken place and as such the measure has fallen to below its 2003 level.

Source: Hallissey (2016)

4. Thresholds and visualisation

Having compiled an initial set of indicators and categorised them by intermediate objective, a number of further steps can be taken to maximise their effectiveness. This section discusses work regarding indicator thresholds and visualisation methods, which aim to highlight risks as they are captured by indicators.

4.1 Thresholds

As touched upon in Section 2.1, the usefulness of an indicator can be enhanced by establishing levels of systemic risk associated with a given indicator value. This is often done by establishing threshold values. Ideally, a threshold should form a dividing line between indicator values associated with a stable financial system and those associated with excessive systemic risk. However, financial crises are infrequent or "tail" events resulting in a limited number of historical



Source: Money and Banking, CSO.

observations. This makes it difficult to construct statistically sound thresholds. As such there is no universally agreed upon approach to threshold calculation and a number of approaches have been taken internationally.

The literature on early warning indicators for financial crisis provides a number of models for threshold calculation, such as the signal extraction method laid out in Drehmann, Borio and Tsatsaronis (2011) and Borio and Drehmann (2009). This method examines the behaviour of indicators in the period preceding past financial crises and an indicator is considered to be "signalling" if it is above a given threshold. An indicator's performance is then assessed by examining the ratio between correct predictions and false warnings across a range of thresholds. Thresholds can then be chosen at levels which maximise an indicator's performance in both areas.¹⁷ The effectiveness of this method can be undermined by the infrequent nature of financial crises which makes it difficult to establish statistically sound thresholds on an individual country basis.

Thresholds can also be established by examining an indicator's historical or cross country distribution and identifying points which may reflect normal or stable conditions, such as average values. As discussed in relation to the credit-to-GDP trend in Section 3.1, this method is purely statistical and average values will not always coincide with sustainable indicator levels. This may be caused by structural change in the economy over time or the effect of consistently extreme values both before and after financial crises. Similarly, cross country comparisons may not take into account structural difference across countries.

A third approach is to refer to both the early warning indicator literature and thresholds put forward by international policy setting groups. While much of the existing literature examines the effectiveness of indicators without establishing optimal thresholds, work by Lo Duca and Peltonen (2011), Drehmann, Borio and Tsatsaronis (2011) and Hermanson and Rohn (2015) does highlight specific thresholds at which indicators are particularly effective. A number of policy making bodies have also proposed indicator thresholds such as credit aggregate thresholds put forward by the Basel Committee on Banking Supervision (2010) and ESRB (2014b) for use in CCyB setting.

While the results of these methods should be interpreted with caution, they are still informative. As a result, all of the above approaches have been applied to as many macroprudential indicators as available data will allow. Work in this area will continue as new data sources become available and methodologies advance.

4.2 Visualisation

Once thresholds have been established, a wide range of visualisation techniques can be employed to provide a clear overview of information contained in the indicators. Visualisation techniques are particularly important in this context, given the large number of indicators required to monitor systemic risk

17 Borio and Drehmann (2009) suggest minimising the noise-to-signal ratio subject to at least two-thirds of the crises being correctly predicted. This is due to the ratio's tendency to reach its minimum at quite a high threshold where both noise and signal ratios are very low. Other literature such as Demirgüç-Kunt and Detragiache (1999) has focussed on deriving an optimal trade-off between missing crises and incorrectly predicting crises by minimising a policy maker loss function.

Figure 14: Point in time and time series heatmapping approaches

Macroprudential Indicators Heatmap																				
>1.5 SDs below		>1.0 S belo	>1.0 SDs below			>0.5 SDs below			Threshold				>0.5 SDs above		>1.0 SDs above			>1.5 SDs above		
		Indicator			Threshold				Risk level			Latest Latest obs date		Quarter-on-quarter change		r '	Year-on-year change			
ŧ,	Standard credit gap			Lower threshold for CCB setting (BCBS 2010)						-59			os	Sep-16	¥	-29.9 pps	¥		59.8 pps	
h an	National specific credit gap			Lower threshold for CCB setting (BCBS 2010)					-74.4pps			s	Sep-16	1.9 pps		4	3.7 pps			
e & p	National specific credit growth			Lower threshold for CCB setting (BCBS 2010)					-3.1%				Sep-16	Ψ	-0.1 pps	0.6 pps		0.6 pps		
tigat dit gr	National specific credit to underlying domestic demand			Lower threshold for CCB setting (BCBS 2010)					-76.8p			-76.8pp	os	Sep-16	1	1.5 pps	1		1.4 pps	
: Mit	Household debt gap			Lower threshold for CCB setting (BCBS 2010)			-42.5pps			s	Sep-16	1	0.6 pps	4	0.6 pps					
ive 1 ssive	Household credit growth			Lower threshold for CCB setting (BCBS 2010)				-2.0%				Sep-16	4	0.2 pps	4	1 0.6 p				
oject	Domestic non-financial corporation debt gap			Lower threshold for CCB setting (BCBS 2010)						-31.9pp	s	Sep-16	•	1.2 pps	4		3.1 pps			
8 -	Domestic non-financial corporation credit growth			Lower threshold for CCB setting (BCBS 2010)							-5.5%		Sep-16	÷	-1.2 pps	+	-	0.5 pps		
		Indicator	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	
ŧ	Standa	ard credit gap																		
oreve	Nation	al specific credit gap																		
e & p	Nation	al specific credit growth																		
lit gr	Nation	al specific credit to underlying de	omestic demand																	
Creck	8 House	hold debt gap																		
ive 1 ssive	House	hold credit growth																		
bject	Domes	stic non-financial corporation deb	bt gap																	
<u> </u>	Domes																			

A grey fill is used where data is not yet available.

Source: Central Bank of Ireland. Note: The above provides a non-exhaustive sample of indicators and time periods covered by the macroprudential heatmaps.

in a modern financial system. As the number of indicators employed by the Central Bank increases, so does the need to synthesise the information they contain.

A popular approach to this type of risk visualisation is heatmapping, which aims to highlight elevated or increasing areas of risk and allow for comparison of risk levels across time periods. The approach has been put forward by both the Banco de España and the Federal Reserve Bank of New York to monitor systemic risk (see Mencía and Saurina (2015) and Adrian, Covitz and Liang (2014)).

The Central Bank has developed a two-part heatmap which provides both a point-in-time and a time series overview of systemic risk in the Irish financial system, as captured by the indicators. These maps assign a risk level to each indicator based on its number of standard deviations from its threshold; a heatmap is then formed by assigning graduated colours to each risk level.¹⁸ For example, an indicator which is more than 1.5 standard deviations above its threshold is assigned dark red and an indicator which is at or just below (0.25 standard deviations) its threshold is assigned light green. This aims to give an immediate overview of the macroprudential risk landscape and to highlight areas of possible concern to policy makers.

The point-in-time map (Figure 14) provides heatmap colour coding for the most recent observation of each indicator along with the value of the observation, its quarter-on-quarter change and its year-on-year change. This provides policy makers with a one-page summary of the indicators, the risks levels these imply and the direction of their movement. The time series map, also shown in Figure 14, uses colour coding only and shows indicator risk levels from 1995 to the most recent period, where data is available. This provides historical context for the risk levels conveyed by indicators and a dynamic picture of the risk landscape. Both heatmap approaches can also be seen in the Central Bank's most recent CCyB rate announcement, where the methodology has been applied to key indicators used in CCyB setting.

While these techniques provide a useful overview of a large number of indicators they have some limitations. They rely on thresholds which, as

¹⁸ Again it should be noted that number of standard deviations from threshold is a purely statistical measure. While assigned colours are based on the general association of above-threshold indicator levels with elevated levels of systemic risk, these colours are not directly linked to a fixed probability of financial crisis occurrence.

discussed earlier, should be interpreted with caution. Moreover, a number of the indicators are simply not suited to being represented by a single number or colour, such as cross-bank exposure matrices. Due to the complexity of systemic risk and of the financial system, as discussed in Section 2.2, visualisation methods should be considered as a starting point of macroprudential analysis and a means of focusing policy maker discussion. They should not be seen as policy setting tools in and of themselves.

5. Conclusion

Monitoring systemic risk is at the core of the Central Bank's responsibilities as a macroprudential authority. However, due to the multifaceted and dynamic nature of systemic risk, this is not a straightforward process and requires a broad range of indicators and methodologies. As part of its systemic risk monitoring framework, the Central Bank has leveraged data available to it as a macroprudential, monetary and supervisory authority and has compiled over 80 macroprudential indicators which are centrally stored in a purposefully structured database. In addition to mapping indicators onto intermediate policy objectives through this database's structure, visualisation methods have been employed to allow the indicators to effectively support focussed policy discussion and decision making. While the indicators are used throughout the policy making cycle, it is important to note that they are not tied mechanically to instrument selection or calibration and that policy maker judgement also plays a central role. The suite of indicators will evolve over time, as new data sources become available, new risks are identified and threshold calculation methods are further developed.

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