Discussion of "Anchoring Countercyclical Capital Buffers: The Role of Credit Aggregates"*

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1. Introduction

A tree's risk of catching fire is usually small, except when the forest is ablaze. It is hardly surprising that the international scope of the recent financial crisis has renewed efforts at designing bank capital regulation to account for both idiosyncratic and systemic risk. I say renewed because crisis prevention policies have been at the forefront of these discussions for quite some time. Almost ten years ago to the date, the Bank of England hosted a conference on "Banks and Systemic Risk" in which Howard Davies, then Chairman of the recently created Financial Services Authority in the United Kingdom, gave an overview on the use of variable capital requirements as a tool against systemic risk (see Davies 2001), the focus of the Drehmann, Borio, and Tsatsaronis paper in this issue (in the context of Basel III), which I will now discuss.

The enduring desire to endow regulation of a macroprudential orientation serves to highlight the difficulty in drawing up rules to satisfy a set of statutory objectives. The turning points and intensity of the financial cycle are not directly observable, a considerable complication for designing variable countercyclical capital buffers, whose justification needs to be specially transparent and unambiguous.

Moreover, supervisory standards should be shared globally to avoid "regulatory arbitrage." Thus, as the winds of the recent

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financial storm died down, the gulf between American and British views on minimum capital standards have increasingly widened. Whereas in the United Kingdom minimum requirements as high as 15–20 percent form part of the conversation, "here [meaning in the United States], that thought is restricted to cranks and university professors. . . . The banks decry any contemplation of an increase in capital standards as a death knell for economic growth" (Eisenger 2011).

Against this backdrop, it is worth remembering that the last thirty years represent an unprecedented period in the financial history of the twentieth century. A study of fourteen advanced countries over the last 140 years by Schularick and Taylor (forthcoming) demarcates three phases of financial development. From the 1870s until the 1940s, the ratio of bank loans to GDP remained very stable at around 50 percent. That stability contrasts with the numerous financial events experienced, culminating in the Great Depression. After World War II and up to the fall of Bretton Woods and the first oil crisis, these advanced economies experienced a period of unprecedented calm—no crisis events are recorded in their sample—with a moderate trend toward increased but strongly regulated financial intermediation coupled with economic growth.

What about the last thirty years? In the United States, the sum of all financial sector claims on the economy relative to annual output stood at about 150 percent in 1975. By 2008 that number had ballooned to about 350 percent (*Economic Report of the President* 2010)—far above pre–Great Depression highs. In the United Kingdom, the total balance sheet of the financial sector amounted to 34 percent of GDP in 1964, yet by 2007 it had reached 500 percent (Turner 2010). By 2008, the ratio of bank loans to GDP in the Schularick and Taylor (forthcoming) data had swelled to 200 percent from 50 percent earlier on. These numbers are coupled with the resurgence of financial crises after the post–World War II oasis of calm that culminated with the well-known events of 2007–08. Yet average growth of output from 1945 to 1975 across all fourteen countries in the Schularick and Taylor (forthcoming) paper is double the growth rate in the thirty years after 1975. In the words of Lord Turner (2010), "There is no clear evidence that the growth in the scale and complexity of the financial system in the rich developed world over the last 20 to 30 years has driven increased growth stability." And Hume and Sentance (2009) have pointed out the stagnant or falling rates of aggregate investment despite the sharp rise in outstanding credit volumes. It would be premature to conclude that the bankers' views on bank regulation are nothing short of farcical and self-serving, but prima facie evidence suggests capital requirements are more "tonic" than "death knell" for economic growth.

Schularick and Taylor (forthcoming)—and, in an extension that includes external imbalance, Jordà, Schularick, and Taylor (2011)—find that credit growth relative to GDP is the best predictor of a financial crisis, with external imbalances a natural concomitant factor in the financial events prior to World War II, but not since. And this finding meshes well with the findings of Repullo and Saurina (2011), who argue that the cyclical properties of credit growth (rather than the credit-to-GDP gap) are better suited to design a mechanical rule for countercyclical buffers: credit-to-GDP gap is negatively correlated with GDP growth in many countries, implying that a reduction of capital requirements is advised in good times, and an increase in bad times. Credit growth and GDP growth are positively correlated instead.

That external imbalances do not play a role in explaining financial crises does not mean that financial events do not propagate across borders, and in fact, the analysis in Jordà, Schularick, and Taylor (2011) finds evidence of precisely this type of phenomenon using straightforward tools from the analysis of networks. This observation provides a natural link between another strand of literature, that on financial networks (e.g., Gai and Kapadia 2010; Haldane 2009; Haldane and May 2011; May and Arinaminpathy 2010; May, Levin, and Sugihara 2008; and Nier et al. 2007), and Drehmann, Borio, and Tsatsaronis' analysis of idiosyncratic factors in connection to macroprudential indicators. May, Levin, and Sugihara (2008) liken financial systems to the type of network found in ecological systems, where highly connected "large" nodes (read large banks) tend to have their connections disproportionately with "small" nodes, and conversely, small nodes connect with disproportionately few large nodes. Such a network architecture is referred to as "disassortative."

An analysis of the U.S. Fedwire system of interbank flows commissioned by the Federal Reserve Bank of New York (Soramäki et al. 2006) showed that on a daily basis, 75 percent of payment flows involve fewer than 0.1 percent of the nodes and only 0.3 percent of observed linkages between nodes—an example of a highly disassortative network, which tends to be stable except when one of the large nodes fails. In a recent paper, Hale (2011) analyzes data for interbank loans involving nearly 8,000 banking institutions across 141 countries using network tools. Hale (2011) reports evidence that the banking network had become more dense, more clustered, and less symmetric, all of which is likely to have increased its fragility and potential for contagion. Arguably then, regulation aimed at improving the stability of the system against systemic risk would impose capital requirements as a function of the network connectivity features of each institution.

Drehmann, Borio, and Tsatsaronis provide a careful analysis of the policy options for dealing with financial system procyclicality through the use of variable bank capital requirements. While they discuss different schemes by which these requirements could be set, it is their empirical evaluation of possible financial stress indicators that is the most innovative aspect of their analysis and where I will focus my discussion. And in particular, I wish to borrow some standard protocols that are routine in medicine, meteorology, and other sciences as a way to formalize the evaluation of these stress indicators and how their signals should be used to determine appropriate capital requirements by balancing costs and benefits.

2. Financial Cycles

Ideally, a variable capital requirement rule should be as simple to communicate as Taylor's (1993) monetary policy rule is to determine how interest rates should be set in response to inflation and output deviations from target. Within the minimum capital requirement levels set by Basel II and some agreed maximum level, capital requirements could be set as a function of deviations of an observable indicator of leverage and macroprudential risk relative to an ideal target level. Requirements could be raised in response to excess leverage, and capital buffers could be depleted when leverage falls below target. Such a rule would presumably smooth the financial cycle and prevent financial crises altogether. In practice, this is much harder than it looks, since idiosyncratic and systemic factors need to be considered in setting the requirements of each institution. Moreover, what is a good leverage indicator is difficult to determine when the causes of financial events are not always well understood. And of course the rule could be generalized to include other indicators, smoothing, and asymmetries.

As Drehmann, Borio, and Tsatsaronis rightly point out, the onset and the intensity of a financial cycle are unobservable. But neither are business cycles: is a low value of GDP an indication of recession or just a temporary setback in the midst of an expansion? Yet I would argue that the same approach used to date and evaluate business-cycle chronologies can be used to analyze financial cycles. Dates of banking crises are available in Laeven and Valencia (2008) and Reinhart and Rogoff (2009), the sources of the crisis dates used by Drehmann, Borio, and Tsatsaronis. But rather than focusing on singular dates of unfortunate and rarely observed events (depending on the sample, these are events observed less than 5 percent of the time), it may be useful to consider a chronology of financial "recessions" as it were, and such is the approach in Claessens, Kose, and Terrones (2011). In that paper, credit—measured as aggregate claims on the private sector by deposit money banks—is sorted into periods of leverage upturns and downturns using the simple Bry and Boschan (1971) algorithm as refined in Harding and Pagan (2002).

The advantages of this approach are numerous. First, the data can be analyzed raw (in the levels) so there is no need to determine an adequate detrending method, of which several alternatives exist but no unique standard has been agreed upon. Second, the method is robust to the arrival of new data in the sense that the dating of the earlier part of the sample remains unaffected. The same cannot be said of most detrending methods since the trend itself will tend to vary as the sample expands (see Canova 1998). Third, the algorithm is transparent and easy to replicate and does not depend on ad hoc interpretation of the historical record.

In a sample of quarterly data from 1960:Q1 until 2007:Q4 for twenty-one advanced OECD countries, Claessens, Kose, and Terrones (2011) identify 114 periods of financial distress (about 25 percent of the time in their sample), not all of which corresponded to a financial crisis à la Laeven and Valencia (2008) and Reinhart and Rogoff (2009). Many correspond well with business-cycle turning points, but not always. On a per-country basis, financial cycles are observed slightly less frequently than business-cycle recessions. An alternative, but in my view less preferable, approach is provided in Lo Duca and Peltonen (2011).

2.1 Evaluating Chronologies of Leverage Cycles

How good are any of these chronologies and therefore which should be used as a benchmark to determine the best real-time indicators and predictors of future turning points? This task may appear hopeless, since there is no gold standard against which each candidate chronology can be compared. But at least the beginnings of an answer can be found in a recent paper by Berge and Jordà (2011), which examines this exact problem in the context of the National Bureau of Economic Research's (NBER's) dating of peaks and troughs of economic activity.

The intuition of how this can be done consists of thinking about the candidate chronology as an expression of the latent state of the financial cycle. Next, think of observable financial conditions indicators as being generated by a mixture distribution, each state determined by the candidate chronology. Sort the observed data depending on the state and compare the resulting empirical distributions. If the chronology is uninformative, a draw with a high value of the financial conditions indicator will be as likely to have come from one state as from the other. If it is informative, the opposite will be the case. Therefore, a measure of the distance between the two implied empirical distributions of the financial indicator can be used to gauge the sorting abilities of each chronology. The two standard measures available are the Kolmogorov-Smirnov statistic and the rank-sum Mann-Whitney statistic, both of which are described in Berge and Jordà (2011). Of course, one must first identify what indicator or indicators could be used for this purpose. Berge and Jordà (2011) use GDP growth and an economic activity index constructed with a factor model, and a similar approach could be used here on, say, credit growth or a financial conditions index constructed with a factor model that may include credit conditions indicators and asset prices, for example.

3. Evaluating the Anchor Variables: The Correct Classification Frontier

Drehmann, Borio, and Tsatsaronis evaluate candidate *anchor* variables—the nomenclature they use to refer to predictors of financial stress events—relative to their ability to sort when a financial event will occur. Therefore, a crisis signal is issued about an impending financial event if the anchor variables take values above a predetermined threshold. In this section, I would like to expand on two related issues: (i) a formal way to choose this threshold so as to balance the costs and benefits of each alternative, and (ii) a formal statistic of overall signaling ability. The principle at play in this section is the notion that the usefulness of a forecast should be judged by the rewards associated with the actions taken by the agent (in this case, the regulator) as a result of the forecast (see Granger and Machina 2006).

Let y_{t-h} be a candidate anchor variable available at time $t-h$ for $h = 0, 1, 2 \ldots H$, and let $S_t \in \{0, 1\}$ be an indicator of the unobserved financial state of the system, a 1 indicating a crisis (or a financial "recession" as explained earlier). At this point, it is important to remark that the Drehmann, Borio, and Tsatsaronis definition of what constitutes a successful prediction is proper classification of crisis/no-crisis periods within a three-year window. Moreover, they separate the onset of the event from its aftermath. This is not what is standard and not what I advocate here—expansions and recessions are not symmetric either—although the procedures that I discuss can be applied equally. Instead, a prediction on the state at time t can be formed as $\widehat{S}_t(h) = I(y_{t-h} > c_h)$, where $I(.)$ is the indicator function that takes the value of 1 if the argument is true, and 0 otherwise. c_h is the threshold associated with an h-periods-ahead forecast. In my view, it would be preferable to evaluate individually which variables are best for what horizons—for example, as when Berge and Jordà (2011) evaluate the information content of the components of the leading economic indicators index in the United States. For simplicity, however, I present the discussion in terms of $h = 0$ and simplify the notation to $\widehat{S}_t$. There are four possible outcomes associated with the {prediction, state} pair with the following probabilities: $P(\widehat{S}_t = 1|S_t = 1)$ is the *true positive rate* $TP(c)$; $P(\widehat{S}_t = 0|S_t = 1)$ is the *false negative rate* $FN(c)$ or type II error; $P(\widehat{S}_t = 1|S_t = 0)$ is the *false positive rate* $FP(c)$ or type I error; and $P(\widehat{S}_t = 0|S_t = 0)$ is the *true negative rate* $TN(c)$. Clearly, $TP(c) + FN(c) = 1$ and $TN(c) + FP(c) = 1$. These rates all depend on the predictive qualities of y_t and the threshold c chosen.

The decision of which threshold to choose can be analyzed using Peirce's (1884) "utility of the method," which in modern parlance characterizes the expected utility given the costs and benefits of each type of error, ability of the predictor to properly sort the data, and unconditional incidence of the phenomena under study. Specifically,

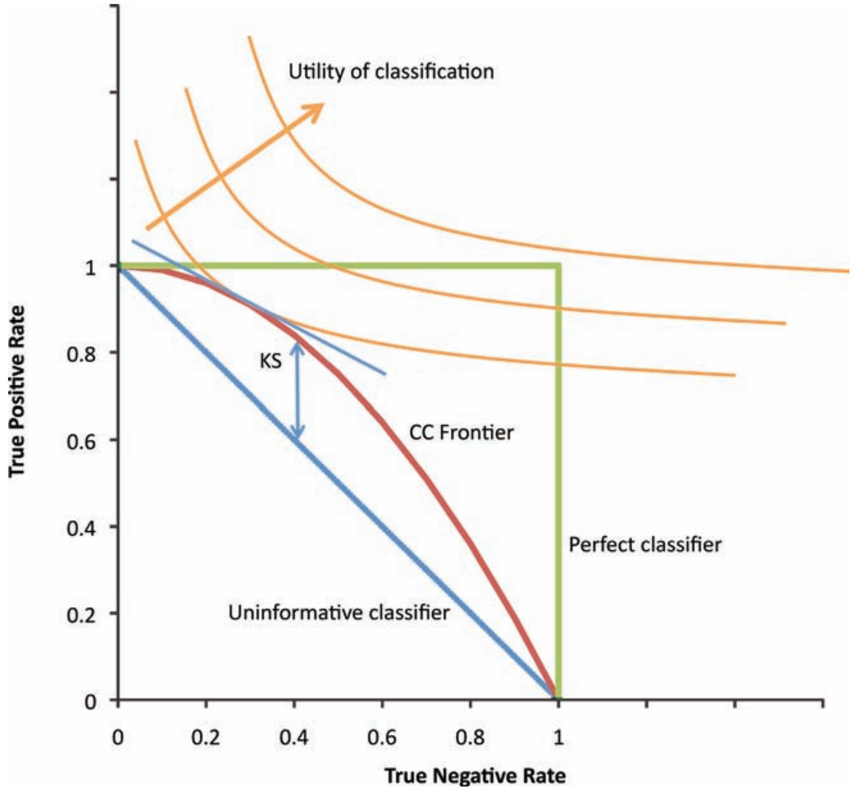
$$U(c) = U_{pP}TP(c)\pi + U_{nP}(1 - TP(c))\pi + U_{pN}(1 - TP(c))(1 - \pi) + U_{nN}TN(c)(1 - \pi), \qquad (1)$$

where $\pi = P(S_t = 1)$, the unconditional probability of a financial event, and U_{aA} for $a \in \{n, p\}$ and $A \in \{N, P\}$ is the utility associated with each of the possible four outcomes defined by the {prediction, state} pair. Notice that since $TP(c) + FN(c) = 1$ and $TN(c)+FP(c) = 1$, everything can be expressed in terms of the true classification rates. Moreover, choosing $c \rightarrow \infty$ will drive $TN \rightarrow 1$ but $TP \rightarrow 0$ and vice versa. Therefore, we can plot the trade-offs in expression (1) by thinking of the combinations $\{TP(c), TN(c)\}$ for $c \in (-\infty, \infty)$ as a sort of production possibilities frontier of correct classification. This curve contains the same intuition as the production possibilities frontier for two goods in standard microeconomics, here the two "goods" being $TP(c)$ and $TN(c)$. Jordà and Taylor (2011) denominate this curve the *correct classification frontier* (CCF), and it is displayed in figure 1.

The diagonal line running from $(0, 1)$ to $(1, 0)$ is the CCF for an uninformative anchor variable since $TP(c) = 1 - TN(c)\ \forall c$. Conversely, an anchor variable with perfect sorting abilities has a CCF that hugs the northeast corner of the $[0, 1]\times[0, 1]$ square. In that case, the relative utility weights become irrelevant because one obtains a corner solution. But in real situations, the CCF will be between these two extremes. As an example, I calculated the CCF for the real credit growth indicator in Drehmann, Borio, and Tsatsaronis, which is similar to the credit growth indicator used in Jordà, Schularick, and Taylor (2011) and Schularick and Taylor (forthcoming) with good success. This CCF is displayed in figure 2.

Further interpretability can be gained by assuming that $U_{pP} = -U_{nP}$ and $U_{nN} = -U_{pN}$; that is, think of U_{pP} as the loss of output (relative to some norm) due to a crisis, and U_{nN} as the loss of output avoided due to unnecessary capital requirements in financially calm times. In that case, the utility function can be plotted against the CCF as is done in figure 1. The optimal choice of threshold c then becomes the tangent between the CCF and the utility function,

Figure 1. The Correct Classification Frontier

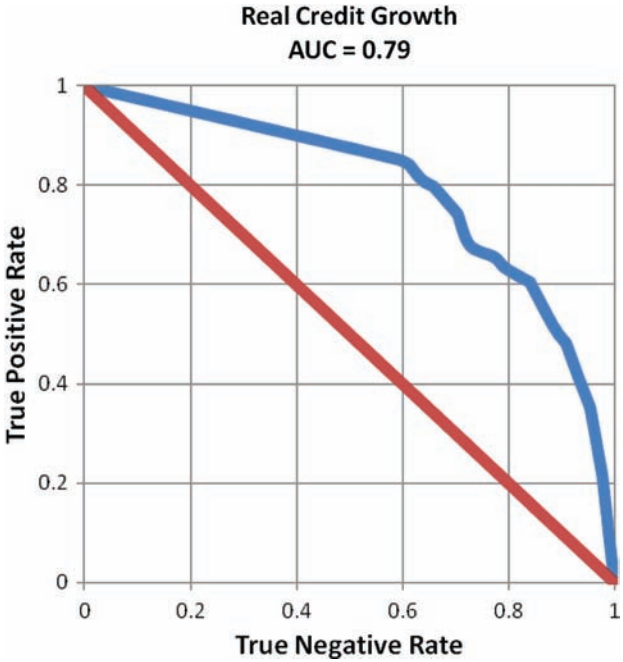


Note: KS refers to the Kolmogorov-Smirnov statistic and is the maximum distance between the CCF and the diagonal line.

which occurs when the slope of the CCF (which is the likelihood ratio of the distributions implied by the state S_t) is equivalent to the expected marginal rate of substitution between output losses due to crises and output losses due to superfluous regulation.

More texture to this analysis can be gleaned from the literature. For example, Jordà, Schularick, and Taylor (2011) calculate that, relative to non-financial crisis recessions, financial crises depress output by an additional 1 percent over a four-year window. On the other hand, Angelini et al. (2011) calculate the impact of the proposed Basel III framework to be in the order of 0.08 to 0.09 percent of

Figure 2. The Correct Classification Frontier for Real Credit Growth



Notes: AUC refers to the area under the CCF and is equal to 0.79. For an uninformative classifier, the AUC is 0.5 and for a perfect classifier, the AUC is 1. Calculated from the data in table 1 in Drehmann, Borio, and Tsatsaronis (this issue).

steady-state output per each percent increase in the requirement. If one assumes it takes nine years to converge to the new steady state, the cost of lower annual GDP growth is 0.01 percent. Clearly the first measure needs to be appropriately renormalized to be comparable to the second one, but at least these numbers can form the beginning of a conversation. And these are not the only sources. For example, the Macroeconomic Assessment Group (2010) at the Bank for International Settlements find that a 1 percent increase in capital requirements implemented over eight years causes a 0.03 percent lower annual GDP growth. The Basel Committee on Banking Supervision (2010) provides yet another set of costs and benefits to draw numbers from.

Yet, even if an agreed-upon characterization of policymaker preferences is hard to come by, the CCF can be used to compute a simple, non-parametric statistic that describes the classification ability of each anchor variable depending on the forecast horizon. This statistic is the *area under the* (CCF) curve, or AUC, and has a long tradition in biostatistics and other sciences (see Jordà and Taylor 2011 for an extensive review of the literature). This statistic can be easily calculated as

$$AUC = \frac{1}{T_N T_P} \sum_{j=1}^{T_N} \sum_{i=1}^{T_P} I\left(y_j^n < y_i^p\right),$$

where T_N and T_P refer to the number of observations associated with the two states 0 and 1, respectively (or "negatives" and "positives"), and $I(y_j^n < y_i^p)$ is just another way of counting the frequency with which values of the anchor variable in the 0 state, y_j^n, attained values that are lower than those attained when the anchor variable is in state 1, y_i^p. The AUC is a Mann-Whitney rank statistic that takes the value of 0.5 for a completely uninformative classifier (the diagonal CCF in figure 1) and the value of 1 for a perfect classifier (with CCF given by the northeast edges of the $[0,1] \times [0,1]$ square). Moreover, under standard regularity conditions (see, e.g., Hsieh and Turnbull 1996),

$$\sqrt{T}(\widehat{AUC} - 0.5) \xrightarrow{d} N(0, \sigma^2),$$

which provides the foundation to construct simple inferential procedures based on the standard Wald principle (see Jordà and Taylor 2011 for an extensive review of testing procedures and ways to estimate σ^2). In fact, most of these methods are available in commonly used econometric packages such as STATA. As an example, I summarize the output in tables 1, 2, and 3 in the Drehmann, Borio, and Tsatsaronis paper using back-of-the-envelope calculations to summarize their findings and with the caveat that they are using a three-year window to claim a successful classification. Thus, this will generate overly optimistic numbers that are reported in table 1.

Table 1 makes it easier to see that the best predictors of financial events are credit-to-GDP gap, property gap, and LIBOR OIS with values of the AUC around 0.8. This value is reasonably high: for

Table 1. The Classification Ability of Candidate Conditioning Variables Using the AUC

Conditioning Variable	AUC	Conditioning Variable	AUC
Credit-to-GDP Gap	0.821	Profits Before Tax	0.712
Real Credit Growth	0.756	Bank CDS	0.535
Real GDP Growth	0.672	Credit Spread	0.730
Equity Gap	0.705	Credit Spread Long T.	0.594
Property Gap	0.821	LIBOR OIS	0.798
NPL	0.584	TED Spread	0.664

Notes: AUC refers to the area under the correct classification frontier. An uninformative classifier has a value of 0.5, whereas a perfect classifier attains a value of 1. The numbers in the table are calculated using the data in tables 1, 2, 3, and 4, in Drehmann, Borio, and Tsatsaronis (this issue).

example, the widely used prostate-specific antigen (PSA) blood test has a similar AUC for detecting prostate cancer (see, e.g., Thompson et al. 2005), and the S&P 500 has an AUC of 0.86 for detecting in current time whether the economy is in recession or not. Similarly, non-performing loans, bank credit default swaps, and the long-term credit spread emerge as the worst indicators with AUC values that, had they not been calculated over three-year windows, would probably be no better than a coin toss.

It is well known that the best predictions are often found by combining the information of all the available predictors, and in this case, this can be easily accomplished by specifying the log-odds ratio of a financial event as a linear combination of anchor variables. Berge and Jordà (2011) use precisely this approach to determine the optimal linear combination of leading economic indicators and show that this linear combination depends heavily on the forecast horizon. This suggests that the de facto aggregation into three-year windows in the Drehmann, Borio, and Tsatsaronis paper may in fact be obfuscating a more clear determination of what anchor variables work and over what horizons.

One final note about the construction of macroeconomic gaps as deviations from a Hodrick and Prescott (HP) trend is worth making. Any monotone transformation of the anchor variable y_t delivers the same CC frontier and hence the same AUC. Unfortunately, the manner in which the trend is calculated, and hence y_t is constructed, does not fall into this category: construction of macroeconomic gaps using different trends will result in different classification ability (or different AUC values). It may well be that there is little difference between HP trends constructed with different values of λ (as the robustness analysis in the Drehmann, Borio, and Tsatsaronis paper indicates), and a value of $\lambda = 400{,}000$ certainly makes the HP trend virtually equivalent to calculating a linear trend. But there are other reasons to find the approach wanting.

To facilitate intuition, think of linear detrending, where the trend is recalculated each time a new observation arrives. Depending on the unknown data-generating process, the most likely outcome is that trend estimates will vary with the sample size. And this will cause gaps calculated earlier to vary, making difficult any retrospective evaluation. Moreover, and as I indicated in the introduction, Repullo and Saurina (2011) suggest that the credit-to-GDP gap moves countercyclically (with output) in many countries, which would seem to suggest contra naturam that capital standards ought to be raised in bad times and lowered in good times. On the other hand, as Repullo and Saurina (2011) point out, credit growth is procyclical and has the advantage of being easy to communicate and stable over time, a desirable feature in a regulatory environment where the regulator is likely to be closely scrutinized.

4. Financial Network Connectivity and Event Detection

My last methodological comment presents a simple way to include the network connectivity properties of individual banks as a way to adjust capital requirements to that bank's systemic relevance within the financial network. There is a substantial but recent literature based on network analysis that suggests that a network's stability depends, in an important and highly non-linear manner, on its topology. Financial networks evolve endogenously, usually with a few large but superconnected clusters of nodes relative to a vast cluster of small but sparsely connected nodes—in the network parlance, a "disassortative" topology. May and Arinaminpathy (2010) explain that such an architecture can endow a network of good stability properties except when one or more of the large nodes gets knocked out. Interestingly, they find the ratio of capital buffers to assets to be relatively smaller in bigger banks than in smaller banks, exactly the reverse of what would seem preferable. This point has been emphasized in a recent speech by Haldane (2009).

Here I would like to offer one approach to constructing and evaluating the virtues of a network connectivity indicator for the purpose of predicting impending financial events and possibly as a variable to be used to determine variable requirements for banks of different import. Jordà, Schularick, and Taylor (2011) use such an approach to examine the international contagion properties of financial crises and find that there is predictive value in knowing if other countries have experienced a crisis in the recent past.

I begin by proposing a way to evaluate how network connectivity of node-level financial events can be used to predict systemic events. Two straightforward network connectivity measures are the *incidence rate*, r_t, and the *wiring ratio*, w_t. In this application, the incidence rate simply measures the proportion of banks experiencing a financial event (where a financial event at the bank level needs to be more precisely defined—but here let's suppose for simplicity, a bank failure) relative to the totality of banks. Thus, let $S_{it} \in \{0, 1\}$, with 1 indicating that bank i has experienced a financial event at time t. Hence define

$$\eta_t = \sum_{i=1}^{n} S_{it}$$

so that $r_t = \eta_t / n$, n being the total number of banks. There are three unsatisfactory features of such a simple measure: (i) it does not account for the size of the institution, (ii) the marginal effect of an additional bank failure is independent of how many banks have failed, and (iii) it does not account for the nature of its pairwise connections to other institutions.

The wiring ratio, weighted by the size of the pairwise connections to other institutions relative to the system, offers a remedy to these three shortcomings. Define the ratio of pairwise connections between "failing" banks to total pairwise connections as

$$w_t = \frac{\eta_t(\eta_t - 1)}{n(n-1)} \in [0, 1]. \tag{2}$$

Before we bring in the weighting, it is clear that the marginal effect of an additional bank failure is quite low when few banks are in distress, but quite high in the alternative. In order to introduce weighting, consider a simple example and thus define g_{it} as some measure of the banks' assets, although some other measure could be used instead. Therefore, a natural weighted version of (2) is

$$w_t^* = \frac{\mathbf{S}_t' G_t \mathbf{S}_t}{(n-1)\sum_{i=1}^{n} g_{it}} \in [0,1], \tag{3}$$

where $\mathbf{S}_t$ is an $n \times 1$ vector with 1's in entries for banks experiencing a financial event, and 0 otherwise. G_t is an $n \times n$ lower triangular matrix with zeroes in the main diagonal and with typical (i,j) entry given by $g_{it} + g_{jt}$ for $i > j$. Thus, the weighted wiring ratio computes the ratio of pairwise weighted connections of banks in distress relative to the total sum of bank-size weighted pairwise connections. Of course, here I am focusing on measures of financial distress connectivity, but one could choose instead connectivity on the basis of interbank flows, for example. The ability of w_{t-h}^* to determine a financial event at time t can then be evaluated using the techniques described in the previous section.

Focusing instead on a bank's connectivity (say, by measuring the flows of interbank payments), a different measure of network connectivity could be constructed as follows. Define Γ_t as an $n \times n$ matrix with typical entry $\gamma_t(i,j)$ representing the payments of bank i to bank j and with $\gamma_t(i,i) = 0$ by construction. Let L_{it} be the i^{th} row of matrix Γ_t, which collects all the entries in which bank i makes a payment to other banks (L is for *liabilities*). Conversely, let A_{it} be the i^{th} column of the matrix Γ_t, which collects all the payments made to bank i (A is for *assets*). Then, the ratio of total payments made and received by bank i relative to the total volume of pairwise payments in the system is

$$\omega_{it}^* = \frac{L_{it}\mathbf{1}_n + \mathbf{1}_n' A_{it}}{\mathbf{1}_n' \Gamma_t \mathbf{1}_n} \in [0,1]$$

and can be seen as a bank-specific wiring ratio analogue to (3), but based on payment flows rather than on defaults.

The measures proposed here are only meant to be illustrative of how network connectivity can be characterized for the purposes of predicting financial events and for the purposes of tailoring capital requirements to institutions so as to account for systemic risk.

Clearly, more work is required in this particular area, although there are some interesting recent estimates in Schwaab, Koopman, and Lucas (2011), who analyze 12,000 firms and extract an estimate of what they label a default risk factor.

5. Summary

Ideally, one would formulate a dynamic stochastic general equilibrium model of the economy with a detailed characterization of how a heterogeneous financial sector affects real activity, how systemic risk can build up and wane, how capital regulation interacts with economic growth, and whether it can be crafted to smooth the financial cycle and prevent financial events. But we are far from having such an understanding and in the meantime the design of a supervisory framework that can meet real and pressing needs must rely primarily on a careful statistical analysis of the data. Drehmann, Borio, and Tsatsaronis have made a decisive contribution in this direction to which I only wish to add a bit of structure to think about the problem more formally.

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