RISEC, Volume 51 (2004), No. 4, 465-476

BANKS' DEFAULT FORECASTS: DO THEY SMOOTH OR AMPLIFY INDUSTRY LENDING CYCLES?

by

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1. *Introduction*

Economists have studied the role of credit supply in business fluctuations for many years. The literature on the subject (see, e.g., Mill, 1848; Juglar, 1860; Marshall and Marshall, 1879; Pigou, 1929; Minsky, 1964; Rajan, 1994; Kiyotaki and Moore, 1997; Asea and Blomberg, 1998) is mostly concerned with *economy-wide* cycles of credit availability and their implications for output fluctuations. In Pigou's view bank credit amplifies business fluctuations in as much as credit provides leverage to entrepreneurs who not only drive the expansion but ultimately, by their excessive optimism, also bring about the contraction. A different way for banks' lending policies to influence an economy is through their effect on credit supplies to various industries of an economy. Hence, this article addresses the issue of *industry lending cycles*. A key behavioral role is played in this process by banks' methods of forecasting the probability of defaults by borrowers (i.e., firms) in different industries. For the present analysis we take the risk of failure of investment projects as a synonym for the probability of loan default. Hence, we abstract from voluntary defaults and the related issues of moral hazard and time inconsistency.

In the past several years banks have made considerable efforts to improve

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I would like to thank an anonymous referee for helpful comments.

the accuracy of their forecasts of default rates by building data bases, by applying modern statistical methods, and by improving the ways of using the expertise of loan and credit officers. Much of our knowledge about this development comes from surveys conducted by the Basel Committee on Banking Supervision (see Basel Committee, 2001).[1] Starting in 1988, this committee has proposed methods for measuring the appropriate capital of banks based on banks' own measures of default risks. Given this purpose, bank regulators are mainly interested in the development of banks' *internal rating systems* for loans. The rating process can be seen as a mapping of the expected probability of default into a discrete number of quality classes (see Krahnen and Weber, 2001). However, banks' use of default rate forecasts goes well beyond the computation of ratings. Profitable allocation of lending to different borrowers and pricing of funds depends critically on the accuracy of default probabilities. As a result, banks typically predict default rates for shorter horizons than is needed for the computation of ratings.[2]

A major factor responsible for defaults is the course of the macroeconomy (for international evidence see Wilson, 1998). The leading measure of output, gross domestic product, is released quarterly and in most countries undergoes several revisions after its initial release. This paper identifies this observational lag as an important reason why banks make their forecasts of default rates by relying on correlations between default series of different industries (see Nagpal and Bahar, 2001). It is this detailed knowledge of economy-wide default data that gives banks a special advantage in assessing the likely success of investment projects. However, producers (borrowers) also have an information advantage over banks. Firms typically have access to information specific to their industry that is not available to outsiders like banks. In forming expectations firms incorporate information that is at least partially gathered by producers' associations. Hence, it is interesting to investigate the macroeconomic consequences of the different default forecasting practices of lenders and borrowers. Are banks by basing their default forecasts on information extraction across different industries likely to magnify or dampen lending and investment fluctuations across industries? The model of the next section describes the conditions under which either outcome occurs. It is important to clarify here that what is meant by industry fluctuations are not changes or cycles per se but rather *inefficient* fluctuations or cycles. Hence, we explore the question whether banks' default forecasts

[1] See Altman and Saunders (1997) for a general survey of developments in credit risk measurement.

[2] The point-in-time approach proposed by the Basel accord assumes that ratings are based on a 12 month forecast horizon.

move lending closer to or farther away from the efficient level. Thus, here the dampening of the lending cycle means reducing the deviations from the efficient level of lending whereas amplifying means increasing the deviations from the efficient credit allocation.

2. *The Model*

We study an economy with two industries A and B. The fraction of defaulting loans in any industry (d^A and d^B) is affected by a general factor (denoted by Y) and by industry-specific factors. The general factor or condition (e.g., GDP) is observable but only with a lag of one period. This means that at time t we have Y_{t-1} as the latest available measure. The industry-specific factors are partly observable by everybody (and thus irrelevant for the present analysis) and partly only observable by firms active in the specific industry. Specifically, firms in an industry are understood to have access to an index of orders or sales of that industry (denoted I_t^A and I_t^B, respectively) relevant for forecasting defaults that is gathered by producers' associations. Hence, this is where firms (borrowers) have information that is superior to that of banks. Banks, on the other hand, have an information advantage since they have a constant inflow of information regarding defaults across the whole industrial sector. That is, a typical bank has information on d^A and d^B whereas a producer only learns about his own industry's d. The analysis that follows will show how these information differentials lead to a different outlook regarding defaults on the two sides of the credit market. We assume that default rates across industries are *not directly linked* in order to make clear that information from another industry can become relevant for assessing the course of a particular industry even when these industries are not causally linked. Specifically, the laws of motion are: [3]

$$d_t^A = -\alpha_1 Y_t - \alpha_2 I_{t-1}^A + \varepsilon_t^A \tag{1}$$

$$d_t^B = -\beta_1 Y_t - \beta_2 I_{t-1}^B + \varepsilon_t^B \tag{2}$$

$$Y_t = \theta Y_{t-1} + \varepsilon_t^Y \tag{3}$$

[3] The series I_{t-1}^A and I_{t-1}^B have to be thought of as being orthogonal to Y_t.

Here Y is the deviation of output from its trend and all other variables are understood as deviations from their steady state levels. We now turn to the default forecasts of banks and firms in detail. To repeat the assumptions regarding information availability: firms have access to the index I of their industry.[4] Banks *do not* have that information. In contrast, banks have access to default rates across all industries. Firms *do not* have access to that information and only know their own industry's d. Hence, each type of player has a selective information advantage. The models of defaults that *banks* use start from the following system of (two) equations:

$$d_t^A = -\alpha_1 Y_t + \varepsilon_t^{A,Bank} \tag{4}$$

$$d_t^B = -\beta_1 Y_t + \varepsilon_t^{B,Bank} \tag{5}$$

Expressed in observable variables and residuals this system can be written as

$$d_t^A = -\alpha_1 \theta Y_{t-1} - \alpha_1 \varepsilon_t^Y + \varepsilon_t^{A,Bank} \tag{6}$$

$$d_t^B = -\beta_1 \theta Y_{t-1} - \beta_1 \varepsilon_t^Y + \varepsilon_t^{B,Bank} \tag{7}$$

This setup gives rise to an information extraction problem for a bank where the innovation in Y_t can be estimated on the basis of d_t^A and d_t^B. The solution of this problem is as follows: assuming independence and identical variances for ε_t^A and ε_t^B, the banks' maximum likelihood estimate of ε_t^Y (i.e., computing the estimate $\hat{\varepsilon}_t^{Y,Bank}$) means minimizing the sum of squares $\left(\varepsilon_t^{A,Bank}\right)^2 + \left(\varepsilon_t^{B,Bank}\right)^2$, where $\varepsilon_t^{A,Bank}$ and $\varepsilon_t^{B,Bank}$ are computed from (6) and (7), respectively. Solving the first order condition yields

$$\hat{\varepsilon}_t^{Y,Bank} = -\frac{\alpha_1}{\alpha_1^2 + \beta_1^2} d_t^A - \frac{\beta_1}{\alpha_1^2 + \beta_1^2} d_t^B - \theta Y_{t-1} \tag{8}$$

Rewriting (6) and (7) for period $t+1$, taking expectations as of time t, and

[4] Clearly, firms additionally have an information advantage particularly regarding their own performance. The present analysis abstracts from this heterogeneity of information on the individual level.

inserting (8) we find the values of $E_t\left(d_{t+1}^A \middle| Bank\right)$ and $E_t\left(d_{t+1}^B \middle| Bank\right)$, that is, the expectations conditional on the agent's information set:[5]

$$(9) \qquad E_t\left(d_{t+1}^A \middle| Bank\right) = \theta \frac{\alpha_1^2}{\alpha_1^2 + \beta_1^2} d_t^A + \theta \frac{\alpha_1 \beta_1}{\alpha_1^2 + \beta_1^2} d_t^B$$

$$(10) \qquad E_t\left(d_{t+1}^B \middle| Bank\right) = \theta \frac{\beta_1^2}{\alpha_1^2 + \beta_1^2} d_t^B + \theta \frac{\alpha_1 \beta_1}{\alpha_1^2 + \beta_1^2} d_t^A$$

The two equations indicate that with a positively autocorrelated general factor (this is the empirically relevant case), from the perspective of the bank there is a *positive information spillover* from either industry to the other. A positive information spillover means that a high level of d in one industry raises the bank's forecast of the other industry's d. In the dynamic setup studied here these spillovers are symmetric as indicated by the identical coefficients capturing the cross-industry effects in equations (9) and (10). The described forecasting scheme at times leads to situations where a purely idiosyncratic shock in one industry (e.g., ε^A) leads banks to wrongly change their default outlook for both industries. However, probabilistically (i.e., considered over all possible cases) the described mode of extracting information across industries that banks practice is efficient and unbiased.

Firms' expectations are simpler to specify than those of banks since they don't extract information across industries. Specifically, firms' expectations in either industry are:

$$(11) \qquad E_t\left(d_{t+1}^A \middle| FirmA\right) = -\alpha_1 \theta Y_{t-1} - \alpha_2 I_t^A$$

$$(12) \qquad E_t\left(d_{t+1}^B \middle| FirmB\right) = -\beta_1 \theta Y_{t-1} - \beta_2 I_t^B$$

Both the forecast schemes of banks and firms are boundedly rational and are now contrasted with the perfectly rational forecasts that a hypothetically fully informed agent would form. This forecast is the best possible forecast and serves as a *benchmark* for a comparison of the forecast schemes of

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[5] Procedurally, these expectations are formed by running a regression of the type $d_t^A = \phi_1 d_{t-1}^A + \phi_2 d_{t-1}^B$ with historical data of d^A and d^B.

lenders and borrowers. The fully informed forecasts of default rates make use of both the information available in the two industry's d-series as well as the I-series. A perfectly informed agent would forecast based on the following system of equations for defaults expressed in observable variables and residuals:

$$d_t^A = -\alpha_1\theta Y_{t-1} - \alpha_1\varepsilon_t^Y - \alpha_2 I_{t-1}^A + \varepsilon_t^A \tag{13}$$

$$d_t^B = -\alpha_1\theta Y_{t-1} - \alpha_1\varepsilon_t^Y - \alpha_2 I_{t-1}^B + \varepsilon_t^B \tag{14}$$

Minimizing (correspondingly with the problem solved by the bank) the sum of squares $(\varepsilon_t^A)^2 + (\varepsilon_t^B)^2$, we find the fully efficient estimate of ε_t^Y:

$$\hat{\varepsilon}_t^Y = -\frac{\alpha_1}{\alpha_1^2+\beta_1^2}d_t^A - \frac{\beta_1}{\alpha_1^2+\beta_1^2}d_t^B - \theta Y_{t-1} - \frac{\alpha_1\alpha_2}{\alpha_1^2+\beta_1^2}I_{t-1}^A - \frac{\beta_1\beta_2}{\alpha_1^2+\beta_1^2}I_{t-1}^B \tag{15}$$

The (unboundedly) rational forecasts of the two default rates are thus

$$\begin{aligned} E_t\left(d_{t+1}^A\right) = {} & \theta\frac{\alpha_1^2}{\alpha_1^2+\beta_1^2}d_t^A + \theta\frac{\alpha_1\beta_1}{\alpha_1^2+\beta_1^2}d_t^B - \alpha_2 I_t^A \\ & + \theta\frac{\alpha_1^2\alpha_2}{\alpha_1^2+\beta_1^2}I_{t-1}^A + \theta\frac{\alpha_1\beta_1\beta_2}{\alpha_1^2+\beta_1^2}I_{t-1}^B \end{aligned} \tag{16}$$

$$\begin{aligned} E_t\left(d_{t+1}^B\right) = {} & \theta\frac{\beta_1^2}{\alpha_1^2+\beta_1^2}d_t^B + \theta\frac{\alpha_1\beta_1}{\alpha_1^2+\beta_1^2}d_t^A - \beta_2 I_t^B \\ & + \theta\frac{\beta_1^2\beta_2}{\alpha_1^2+\beta_1^2}I_{t-1}^B + \theta\frac{\beta_1\alpha_1\alpha_2}{\alpha_1^2+\beta_1^2}I_{t-1}^A \end{aligned} \tag{17}$$

These rational forecasts can now be used for assessing the role of default forecasts of lenders and borrowers. First, it is clear that forecasts by lenders and borrowers can conflict. Under special circumstances (when firms' industry-specific information has little or no forecast value) banks' assessments are generally superior compared with firms' assessments. In fact when α_2 and β_2 are zero, banks' forecasts are fully rational as can be seen by verifying that under these circumstances equations (16) and (17) reduce to (9) and (10). However, when α_2 and β_2 are larger than zero either lenders' or borrowers' assessment are more accurate at any point in time.

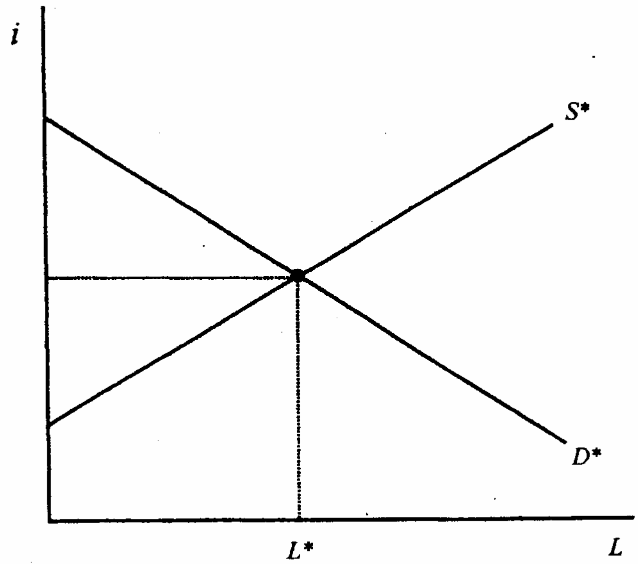

Figure 1. The market for loans to borrowers of the same industry

In order to evaluate the effects of these different predictions we use a simple model of the credit market. In this model credit is allocated without credit rationing, that is, the interest rate is the equilibrating variable. Specifically, we look at the market for credit to producers in *one* industry. Figure 1 shows the basic demand and supply framework for loans (L) to firms in this industry as a function of the interest rate on these loans (i).[6] Both the demand for credit and the supply of credit depend on the likelihood of success of investment projects (i.e., on the probability of default). On the one hand, the probability of business failure affects the demand for loans because it (negatively) affects the expected return on the *capital* of the investing firm. On the other hand, the probability of business failure affects the supply of credit because it (negatively) affects the expected net payoff to the bank. Hence, an increase in the expected rate of default shifts both the supply and

[6] Clearly, the interest rate determined in different industries will not be the same particularly due to the differences in the expected rate of defaults in different industries.

the demand curve to the left while a reduction of the expected probability of default shifts the two curves to the right.

The curves in Figure 1 should be thought of as the supply and demand functions in the *hypothetical* (unrealistic) case where both lenders and borrowers would form expectations in a fully informed way, that is, according to equations like (16) and (17). These curves are denoted with an asterisk (S^* and D^*) and their intersection is referred to as the *full information equilibrium*. Absent distortions on the credit market this equilibrium would be the socially efficient outcome. Changes in default rates as well as changes in the industry indexes across the economy will lead to shifts in the curves drawn. For presentational purposes, however, we assume that the fully rational default forecast is constant and investigate the effects of variations in the default expectations of the two boundedly rational players on the credit market.

In order to simplify the presentation of results, we distinguish four scenarios. Figure 2 shows the four selected cases. Panel a) of this figure illustrates the case where both banks and borrowers are overly optimistic in their default forecasts.[7] This is identified in the figure with the superscripts *oo* standing for "over-optimistically". In this case the supply of lending is inefficiently large compared to the full information equilibrium. This is a case where banks amplify the deviation from the efficient level of lending. The interest rate can be higher or lower compared to the full information equilibrium. Panel b) shows the situation where an overly optimistic view on the side of borrowers meets an overly pessimistic (identified by the superscript *op*) outlook of banks. In this case it is possible that exactly the right amount of lending goes to the specific industry (this is the special case drawn in the figure). However, it is also clear that in this situation borrowers will agree to a lending rate that in retrospect they judge as excessive. Panel c) shows the opposite case where overly pessimistic expectations on the side of borrowers are combined with overly optimistic expectations of banks. Here, as in the previous case, banks dampen the intended excess of borrowers. The difference with respect to the case discussed before is that here banks settle for a lending rate that with hindsight they judge as insufficient. Finally, panel d) shows the situation where both lenders and borrowers are overly pessimistic. In this case lending certainly falls short of the efficient level, and banks amplify the inefficient deviation from the socially optimal level of lending.

[7] One combination of economic circumstances that would result in over-optimism by both borrowers and lenders of industry A would be an increase in d_t^B (leaving borrowers overly optimistic) and a decrease in I_t^A (leaving lenders overly optimistic).

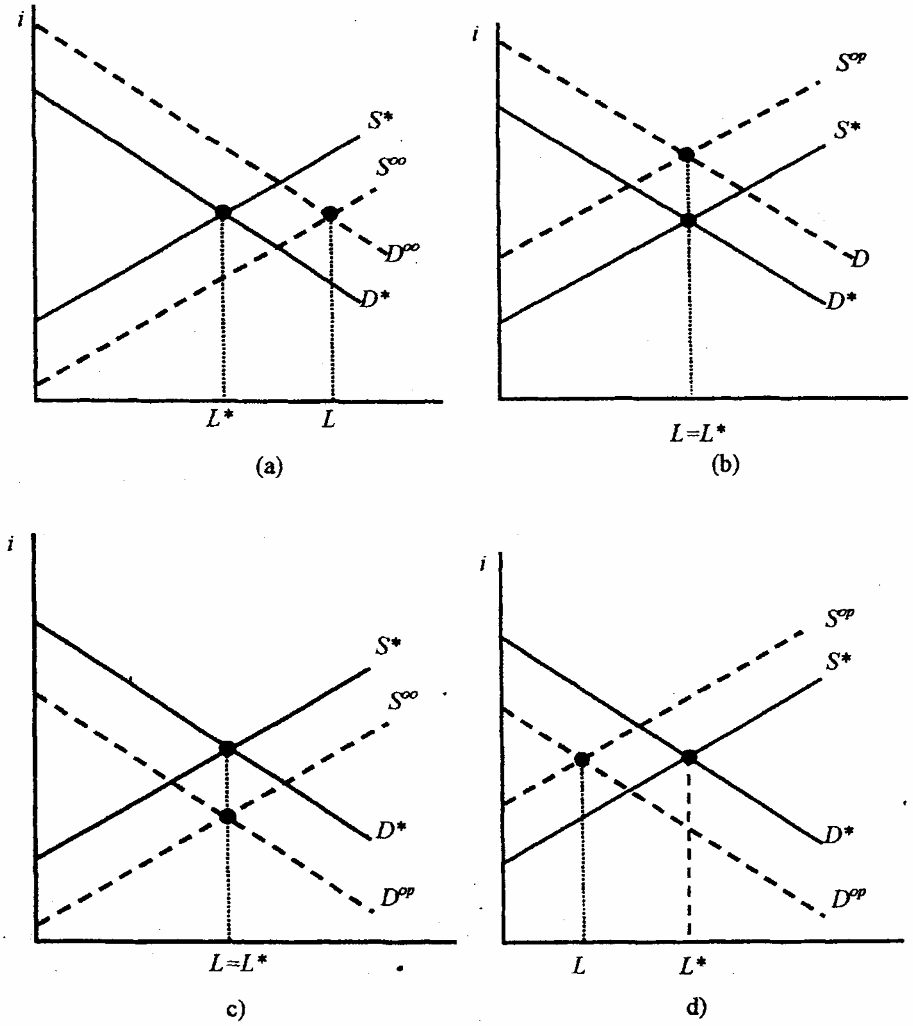

Figure 2. The market for loans with different expectations of banks and borrowers

Grouping the different possible cases we can say that banks *amplify* industry cycles (i.e., intended excesses of borrowers) whenever banks and borrowers err on the same side of the fully rational default forecast. Banks possibly *stabilize* industry cycles when lenders and borrowers err on different sides of the fully rational forecast. However, the difference in the sign of the two errors is not a sufficient condition: Figure 3 presents a possible case where the size of banks' misjudgment is so large as to over-compensate the error on the side of borrowers. This is one more case where bank lending amplifies the industry cycle.

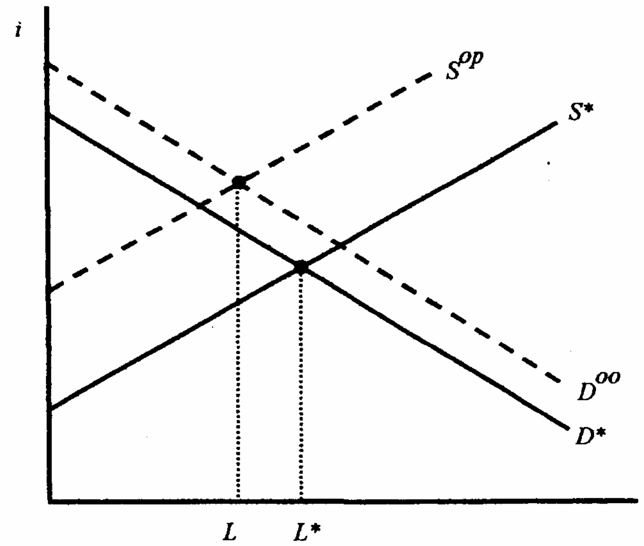

Figure 3. A case of destabilizing lending due to banks' erroneous default forecasts

Finally we want to address the question how the modern procedure of banks' to systematically extract default information across industries affects industry fluctuations and lending efficiency overall. When banks do not (or did not) perform cross-industry information extraction (as captured by equations 4 through 10) banks' industry default forecasts rest on nothing but the effects of general business conditions on each industry (i.e., $-\alpha_1\theta Y_{t-1}$ and $-\beta_1\theta Y_{t-1}$, respectively). In this situation the forecasts of banks are systematically less accurate than the predictions of lenders (because firms have a clear information advantage). Hence, banks mostly err on the same side as borrowers but by a wider margin. Under these circumstances instances where banks stabilize lending can still happen. However, stabilizing effects from the side of lenders are less frequent than in a world where banks use independent information. Hence, banks' improvements in default forecasting practices are socially beneficial.

3. *Conclusions*

Contrary to Pigou's notion that banks generally support the excessive expectations of producers with their provision of funds, this analysis suggests alternating situations where banks' lending policies either stabilize or destabilize lending. Current innovations in banking regulation and increasing competition among banks are promoting increasing sophistication in banks' default forecasting procedures. These developments help to increase banks' ability to allocate credit efficiently and to stabilize industry cycles. Public policies that lead to the provision of better and timelier data of aggregate and industry variables are also important. Better economic data improves accuracy of both borrowers' and lenders' predictions and also helps to allocate lending efficiently.

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ABSTRACT

Banks are lenders to businesses in various industries and thus have a wider base of information regarding default rates than their borrowers. In contrast, borrowers (i.e., firms) have an information advantage, particularly with respect to the performance of their own industry. This article shows how the different information sets on the two sides of the credit market lead to different forecasts of default rates. Contrary to Pigou's notion that banks generally support the excessive expectations of producers with their provision of funds, this analysis suggests alternations of situations where banks' lending policies either smooth or amplify industry lending fluctuations. Overall, banks' improvements in default forecasting practices are socially beneficial.

JEL classification: *E44, F34, G21*
Keywords: *bank lending, industry cycles*