

The Impact of Banking Sector Stability on the Real Economy[★]

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Abstract

This article studies the relationship between the degree of banking sector stability and the subsequent evolution of real output growth and inflation. Adopting a panel VAR methodology for a sample of 18 OECD countries, we find a positive link between banking sector stability and real output growth. This finding is predominantly driven by periods of instability rather than by very stable periods. In addition, we show that an unstable banking sector increases uncertainty about future output growth. No clear link between banking sector stability and inflation seems to exist. We then argue that the link between banking stability and real output growth can be used to improve output growth forecasts. Using Fed forecast errors, we show that banking sector stability (instability) results in a significant underestimation (overestimation) of GDP growth in the subsequent quarters.

Key words: Banking sector stability, real output growth, output growth forecasts.

JEL classification: E20, E44, G21.

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1 Introduction

The increased incidence of banking and financial crises over the last quarter century has triggered an active research agenda, not only on the underlying causes of crises, but also on their impact on the real economy. Literature in this field has been mainly focussed in two directions: first, on understanding links between banking sector characteristics and long term growth and, second, on quantifying the costs of banking sector crises in terms of real output losses. In the first strand of research, Levine (1997, 2001) demonstrates the link between the openness of the banking sector and economic growth. Several other authors (Levine, 1997, 1998, Levine, Loayza, and Beck, 2000, King and Levine, 1993a,b, Demirgüç-Kunt and Maksimovic, 1998, Rajan and Zingales, 1986) have highlighted that the degree of development in the financial sector acts as an important contributor to economic growth.¹ The second strand of research reaches a clear conclusion: banking crises have usually coincided with, or preceded, a substantial economic slowdown (see among others Hogart, Reis, and Saporta, 2002, Boyd, Kwak, and Smith, 2005, Serwa, 2007, Kroszner, Laeven, and Klingebiel, 2007, Dell’Ariccia, Detragiache, and Rajan, 2008). The literature is however, far less clear regarding whether or not the banking sector is the main trigger of the economic slowdown, as it is difficult to separate cause and effect in the financial sector real economy nexus (Kaminsky and Reinhart, 1999, Demirgüç-Kunt and Detragiache, 1997, 2005, Hilbers, Otter-Robe, Pazarbasioglu, and Johnsen, 2005). These empirical conclusions have prompted an increased interest in both policy makers and academics to assess, from a theoretical point of view, the extent to which macroeconomic policies and banking system soundness depend on one another (Benink and Benston, 2005, Gupta, 2005, European Central Bank, 2006, Deutsche Bundesbank, 2006, Goodhart, Sunirand, and Tsomocos, 2006).

This paper clearly belongs to the second strand of research. Indeed, we are not concerned by the effect of financial development on long term growth, but rather by the (possibly transitory) impact of banking sector instability on real output growth. We are also not interested in investigating the events at the roots of banking sector instability *per se*, and thus we take banking sector instability as given, without examining its causes. One flaw of the studies cited above in the second strand of research is that they focus solely on the loss in output growth during or after banking *crises*, ignoring the banking sectors impact during more stable times.² The main reason for this is that many authors have chosen to work with binary dependent variables (crisis vs. non crisis). However, several drawbacks are associated with adopting this approach. First, bank crises are relatively rare events. Second, the choice of

¹ This literature is reviewed in Levine (2004).

² One exception to this is Rancière, Tornell, and Westermann (2008) who shows a positive link between average growth and banking sector instability.

threshold for defining a crisis is highly discretionary. Finally, binary variables impose the unrealistic assumption that a banking sector that is not experiencing a crisis is necessarily healthy. The focus on crises vs. non crisis periods has consequently resulted in a lack of research into the impact of the banking sector on the real economy in less extreme times. It remains unclear whether 'normal' reductions in banking sector stability – i.e. a level of instability that can regularly be observed but that does not translate into a banking crisis – have a significant impact on growth.³

In this paper, we contribute to the literature by empirically assessing whether the degree of banking sector stability has an impact on the real economy in non extreme times. In particular, we are interested in determining whether a period of banking sector instability is followed by reduced real output growth in the subsequent quarters. We measure banking sector stability based on the banking sector's probability of default. This measure has the advantage of being continuous by nature and thus captures a continuum of states, rather than classification as either crisis or non crisis. This contrasts with the binary variables approach usually adopted in this context. In contrast to other distance-to-default measures previously used, our measure allows for a time-varying volatility for banks assets. Following Aspachs, Goodhart, Tsomocos, and Zicchino (2007), we explore the impact of banking sector stability on real output growth and inflation rates in the subsequent quarters with a *panel vector autoregressive model*⁴. Our sample consists of quarterly data for 18 OECD countries over the 1980-2008 period. The novelty of our set-up is that it allows the variance of output growth to be dependant of the state of the banking sector. This captures the impact of banking sector instability on output growth as well as on its uncertainty.

Our results can be summarized as follows: banking sector stability is an important driver of future GDP growth. Periods of stability are generally followed by an increase in real output growth and vice versa, a finding which appears to be driven predominantly by periods of relative instability rather than by periods of stability. In addition, we show that banking sector instability is followed by higher uncertainty about output growth.

The link between banking sector stability and economic activity is of particular interest to policy makers which base their monetary policy decisions on economic forecasts. Research focussing on understanding whether financial stability should be considered in the setting of monetary policy has investigated the

³ For example, consider a banking sector which suffers credit losses in a business cycle downturn but which is still able to function without external help. The stability of such a banking sector has clearly decreased after credit losses, but since it is still functioning, it is not in a fully fledged crisis either.

⁴ Allenspach and Perrez (2008) study interactions between the banking sector and the real economy for Switzerland via a VAR approach, however it is a single country study that does not make use of the panel VAR methodology adopted here.

informational advantages of the central bank, and in particular whether bank related information can be used to improve macro forecasts. Peek, Rosengren, and Tootell (1999, 2003), Romer and Romer (2000) show that incorporating confidential supervisory information about bank health improves central bank forecasts of both unemployment and inflation, and that in fact, the Federal Open Market Committee (FOMC) consider this information when setting monetary policy. We contribute to this literature by extending our analysis further and investigating the results uncovered thus far. In particular, our results indicated an apparent importance of banking sector stability on output growth. We continue by assessing whether additional information embedded in our stability index might help to improve output growth forecasts. Using Feds forecasts data, we show that banking sector stability (instability) results in a significant underestimation (overestimation) of GDP growth in the subsequent quarters. This finding indicates that additional information embedded in our stability measure has the potential to further improve economic forecasts.

The rest of this paper is organized as follows. Section 2 defines our measure of banking sector stability. Section 3 describes the data used. Section 4 estimates the impact of banking sector stability on output and inflation. Section 5 explores the relationship between banking sector stability and central bank forecast errors. Section 6 concludes.

2 Stability index for the banking sector

2.1 Banking sector stability: definition and assumptions

We define the *instability* as *the probability of the banking sector becoming insolvent within the next quarter*. Hence, a lower probability corresponds to greater stability and vice versa. We consider a banking sector to be insolvent if, at the end of the quarter, the market value of the assets owned by all the banks of a country is not sufficient to repay its total debt (i.e. if at time $t + 1$, the total assets A_{t+1} of the banks are smaller than their total debt D_{t+1}). This approach makes the implicit assumption that the banking sector of country i is equal to a single bank, computed as the the aggregate of the balance sheets of banking institutions in that country. Our measure therefore abstracts from any competitiveness considerations.

To compute the default probability of the banking sector i at time t , two elements are required: the distributions of both the asset value and of the debt value at the end of the period, conditional on their initial values at time t . With these two distribution functions, we are able to compute the probability that, at time $t + 1$, the asset value falls below the debt value.

We assume that the asset value of the banking sector follows a geometric Brownian motion characterized by:

$$dA_t = \mu A_t dt + \sigma_t A_t dw \quad (1)$$

where μ is the instantaneous growth rate of assets, σ_t is their instantaneous volatility rate and dw is a Wiener process. We also assume that, between t and $t + 1$, debt grows at the (continuously compounded) growth rate r , which implies the following one-period transition function:

$$D_{t+1} = D_t e^r \quad (2)$$

2.2 Default probability and distance-to-default for the banking sector

To estimate the default probability of a firm (i.e. of the aggregate banking sector in our case), Merton (1974) suggests considering the firm's equity as a call option on its assets. Merton's method is based on the idea that if, at debt maturity, the value of the firm's assets is smaller than its debt, then the firm cannot repay its debt and becomes insolvent. In this case, the firm's equity is worth zero. If the assets are greater than the debt, then the firm repays its debt and the market value of the firm is equal to the difference between the asset value and the debt. Thus Merton's model states that, at debt maturity (i.e. $t + 1$ in our case), the firm's equity is equal to:

$$\max(A_{t+1} - D_{t+1}, 0) \quad (3)$$

By assuming, as stated in section 2.1 that A_t is log normally distributed and that debt is insured,⁵ Merton (1974) shows, using the Black-Scholes option pricing formula, that the initial price E_t of the banking sector's equity is:

$$E_t = A_t \Phi(d_t + \sigma_t) - D_t \Phi(d_t) \quad (4)$$

with

$$d_t = \frac{\ln(A_t/D_t) - \sigma_t^2/2}{\sigma_t} \quad (5)$$

where $\Phi(\cdot)$ is the cumulative normal distribution.

Note that $\Phi(d_t)$ in equation (4) corresponds to the probability of exercising the option (i.e. the probability that the assets A_{t+1} are greater than the debt D_{t+1}). Therefore, the probability of default (i.e. the probability of *not* exercising the option) is equal to $1 - \Phi(d_t)$. One can show (see Bichsel and Blum, 2004) that d_t measures how far, in terms of standard deviations, the banking sector is

⁵ This assumption implies that bank's bonds will yield the risk free rate even in case of default for the bank.

from its default point (i.e. the point where assets are equal to debt). This is why d_t is often called the *distance-to-default*.

Concretely, for the rest of our analysis, we will not work with the default probability directly but we will rather use the distance-to-default d_t . Note that these two measures are equivalent since they are linked by a strictly continuously decreasing function. A lower distance-to-default always implies a higher probability of default. The distance-to-default measure has the advantage of being unbounded, which is convenient for empirical estimations. The default probability on the other hand, is bounded between zero and one.

To compute the distance-to-default with equation (5), we need to know the asset market value A_t , its volatility rate σ_t and the debt D_t . In practice however, only debt is directly observable. To obtain the asset market value, and its variance rate we make use of equation (4) which links the unobserved assets with the observed market capitalization of the banking sector (i.e. its equity value E_t).

2.3 Estimation of the distance-to-defaults with equity market value

Duan (1994, 2000) shows how to estimate the unobserved evolution of the asset value and its variance making use of the observed evolution of market capitalization. In his original paper, Duan (1994, 2000) works with a constant variance; we extend his method to estimate a time-varying variance.

We start by rewriting equation (1) to get the one-period transition density of A_t , which is equal to:

$$\Delta \ln A_{t+1} = \mu - \sigma_t^2/2 + \omega_t \quad (6)$$

where $\Delta \ln A_{t+1} = \ln A_{t+1} - \ln A_t$ and ω_t is white noise with variance σ_t^2 . Furthermore, we assume that the variance follows a GARCH(1,1) process characterized by:

$$\sigma_t^2 = \kappa + \alpha \epsilon_{t-1}^2 + \beta \sigma_{t-1}^2 \quad (7)$$

The unknown parameters are $\theta = \{\mu, \kappa, \alpha, \beta\}$. Duan (1994, 2000) makes use of the fact that for any given set of parameters θ , equation (4) is a one-to-one mapping between E_t and A_t . The parameter set θ can therefore be estimated by maximizing a log likelihood function defined on E_t instead of on A_t . Duan (1994, 2000) shows that the log likelihood function takes the form:

$$L(E_t, \theta) = - \sum_{t=1}^{T-1} \ln \Phi(\hat{d}_t + \sigma_t) - \frac{T-1}{2} \ln(2\pi) - \frac{1}{2} \sum_{t=1}^{T-1} \ln \sigma_t^2 \\ - \sum_{t=1}^{T-1} \ln \hat{A}_{t+1} - \frac{1}{2} \sum_{t=1}^{T-1} \frac{(\Delta \ln \hat{A}_{t+1} - (\mu - \sigma_t^2/2))^2}{\sigma_t^2}$$

where \hat{A}_t is the unique solution to equation (4) for E_t , given that the parameters θ and \hat{d}_t correspond to d_t with \hat{A}_t instead of A_t . Note that the three last terms on the right-hand side of the previous equation would correspond to the log likelihood functions of a GARCH process if the asset value were directly observable. The first term on the right-hand side of the equation corrects this traditional log likelihood function to account for the fact that we must obtain the asset value A_t from the observable equity price E_t via equation (4). The maximization of the log likelihood function can be performed with ordinary maximization techniques.

3 Data

Our dataset consists of debt and market value data between 1980Q1 and 2008Q4 for a sample of 521 banks covering 18 OECD countries.⁶ All data are obtained from Datastream. The debt data are annual and have been transformed into quarterly data by linear interpolation. The quarterly market value is the minimum of daily market values observed during the quarter.⁷

In addition to the data used to calculate the distance-to-default index for each country, we make use of GDP real growth and inflation between 1980Q1 and 2008Q4. The seasonality component in price movement is removed using the X12 method in Eviews.

Figure 1 presents the estimated distance-to-defaults for each country. We assume that in each country, banking sector stability is measured by the relative size of distance-to-default deviations from its own historical mean. In other words, an unusually unstable banking sector corresponds to a distance-to-default that is substantially below the country historical mean. The horizontal lines represent the first and third quartiles of the distance-to-defaults of all

⁶ We selected countries that joined the OECD before 1975 and that are classified as high-income countries by the World Bank. These countries are Australia (17 banks), Austria (10 banks), Belgium (12 banks), Canada (10 banks), Denmark (52 banks), France (47 banks), Germany (32 banks), Greece (21 banks), Italy (50 banks), Ireland (5 banks), Japan (110 banks), Norway (32 banks), Portugal (9 banks), Spain (23 banks), Sweden (7 banks), Switzerland (33 banks), United Kingdom (14 banks) and United States (37 banks). Finland, Iceland, Luxembourg, Netherlands and New Zealand have been excluded because we could not get data for at least 5 banks.

⁷ We additionally experiment by using the average market value observed during the quarter. However the results are not significantly affected and are therefore not presented here for brevity.

countries. These quartiles are used in Section 4.2 to define the thresholds of stability on which we base our assessment. We define three possible states for the banking sector: unstable, stable and very stable. We consider a banking sector to be *unstable* if its distance-to-default is in the first 20% of all distance-to-defaults observed internationally over the period 1980 to 2007. Similarly, we say that the banking sector is *very stable* if its distance-to-default is in the last quartile of the distribution. Finally, a banking sector is *stable* in all others cases.

Figure 2 shows the number of countries with an unstable banking sector in each period. We can observe four periods in which at more than third of the countries simultaneously experience instability in their banking sector: 1987Q4 (Black Monday and the following stock market crisis), 1990Q1 – 1993Q2 (housing crises in several countries), 1998Q3 (Russian and LTCM crises) and in 2008 (subprime crisis).

4 Impact of banking sector stability real output growth and inflation

In order to assess whether banking sector stability is linked to real output growth and inflation we adopt a panel autoregression (pVAR) approach with state-dependent variance. We make use of a pVAR approach predominantly for the reason that the interactions between financial distress and the real economy have not been rigorously identified theoretically. Using a VAR therefore allows us to impose as little a priori theorizing as possible. Moreover, a panel VAR, when compared to a traditional VAR approach, allows us, by using cross sectional data, to increase the number of observations and thus the precision of our estimations. This is particularly useful in our context since episodes of banking sector instability are relatively rare. The choice of a state-dependent variance derives from a preliminary analysis showing that the residuals of a simple pVAR were heteroscedastic. Thus, in addition to studying the impact of banking sector stability on the levels of GDP growth and inflation, our framework allows us to explore its impact on both GDP growth and inflation *uncertainty*.

The pVAR model has the following specification:

$$y_{it} = Ay_{it-1} + Bx_{it} + \mu_i + H_{it}^{1/2}\varepsilon_{it} \quad (8)$$

where y_{it} is a vector of endogenous variables for country i at time t (i.e. output growth, inflation and banking sector stability), x_{it} is a vector of exogenous variables (i.e. oil prices), μ_i is a fixed effect for each country, ε_{it} is a vector of independent error terms normally distributed and H_{it} is a country-specific

FIG. 1. ESTIMATED DISTANCE-TO-DEFAULTS

FIG. 2. NUMBER OF COUNTRIES WITH WEAK BANKING SECTOR

time-varying covariance matrix, which is function of a set of dependent variables z_{t-1} (see below).

To model H_{it} , we adopt a strategy similar to the conditional constant correlation (CCC) of Bollerslev (1990). The covariance matrix can be decomposed as:

$$H_{it} = D_{it}R_iD_{it} \quad (9)$$

with

$$R_i = \begin{pmatrix} 1 & \phi_{i12} & \phi_{i13} & \cdots & \phi_{i1N} \\ \phi_{i21} & 1 & \phi_{i23} & \cdots & \phi_{i2N} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \phi_{iN1} & \phi_{iN2} & \phi_{iN3} & \cdots & 1 \end{pmatrix} \quad (10)$$

where ϕ_{ijk} is a constant country-specific correlation coefficient between variables j and k in y_{it} and

$$D_{it}^2 = \begin{pmatrix} \sigma_{it1}^2 & 0 & 0 & \cdots & 0 \\ 0 & \sigma_{it2}^2 & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & \sigma_{itN}^2 \end{pmatrix} \quad (11)$$

where σ_{itn}^2 is the variance of residuals for country i at time t for the n th variables of y_{it} . Each variance depends of a set of past variables z_{it} through the following function:

$$\sigma_{itn}^2 = \exp(\alpha_{in} + \alpha_n z_{it-1}) \quad (12)$$

where α_{in} is a fixed effect specific to each country and α_n is a common slope. Note that z_{it} can contain some or all variables in y_{it} and x_{it} .

The likelihood function of the pVAR given θ is:

$$L = \prod_{t=1}^T \prod_{i=1}^I \frac{1}{(2\pi)^{N/2} |H_{it}|^{1/2}} \exp\left(-\frac{1}{2} \varepsilon'_{it} H_{it}^{-1} \varepsilon_{it}\right) \quad (13)$$

where T is the number of periods, I is the number of countries and N is the number of variables in each vector y_{it} . The log likelihood function is then:

$$l = \sum_{t=1}^T \sum_{i=1}^I -\frac{N}{2} \ln(2\pi) - \frac{1}{2} \ln |H_{it}| - \frac{1}{2} \varepsilon'_{it} H_{it}^{-1} \varepsilon_{it} \quad (14)$$

The log likelihood can be estimated with traditional maximization techniques. We use a multivariate version of the estimation methodology proposed by Harvey (1976).

The model is estimated using GDP real growth, price level and oil price growth rate data between 1980Q1 and 2008Q4 collected from Datastream.⁸ Note that we standardize⁹ the distance-to-default for each country. With this, we eliminate the difference in distance-to-default level and volatility between countries. This is equivalent to assuming that, in each country, banking sector stability is measured by the relative size of distance-to-default deviations from each country historical mean. In other words, an unusually unstable banking sector corresponds to a distance-to-default that is unusually below the country historical mean, in terms of historical standard deviations.

4.1 Linear impact of banking sector stability

4.1.1 Impact on real output growth

Table 1 displays the estimated coefficients of the pVAR model with a lag of two for the endogenous and the exogenous variables.¹⁰ For clarity, only coefficients related to the endogenous and exogenous variables are presented; fixed effects are omitted. The estimated coefficients show that the relationship between banking sector stability and real output growth is a two way relationship. Real output growth is important for subsequent stability and similarly, banking sector stability is important for subsequent output growth. In particular, our results indicate that higher growth is followed by greater

⁸ We removed the seasonality component in price movement using the X12 method in Eviews.

⁹ A standardized variable is equal to its value subtracted from its mean and divided by its standard deviation.

¹⁰ The number of lags has been chosen with the Akaike Information Criterion.

TABLE 1
 LINEAR IMPACT OF BANKING SECTOR STABILITY
 ON REAL OUTPUT GROWTH

	Level		Variance	
	GDP_t	DD_t	$\log(\sigma_{GDP_t}^2)$	$\log(\sigma_{DD_t}^2)$
GDP_{t-1}	0.2035**	2.2104**	-16.2861**	-3.7156
GDP_{t-2}	0.1982**	0.1754	-6.8144	11.0961**
DD_{t-1}	0.0011**	0.9671**	-0.3239**	0.6499**
DD_{t-2}	-0.0010**	-0.0093	0.0060	0.3483**
Oil_t	0.0006	-0.0495		
Oil_{t-1}	-0.0020**	-0.0397		
Oil_{t-2}	-0.0011	-0.0526*		

*(**) indicates that the coefficient is significant at the 5% (1%) level. Level: estimated coefficients of equation (8) with GDP growth and banking sector's distance-to-default as endogenous variables and oil price yield as exogenous variable. Variance: estimated coefficients for equation (12) with GDP growth and banking sector's distance-to-default as independent variables.

banking sector stability (column 2, row 1) and that banking sector stability induces growth in the subsequent periods (column 1, rows 3 and 4).

The positive impact of banking sector stability on output growth is observable from the impulse-response functions of the estimated pVAR (lower left-hand side panel in Figure 3). Moreover, shocks (both to banking sector stability and to output growth) are more persistent in their effect on banking sector stability than on output growth (right-hand side vs. left-hand side panels of Figure 3). The impulse-response functions also show that the impact of a positive GDP shock on the improvement of banking sector stability is long lasting.

Table 1 additionally presents the estimated coefficients for the output growth and banking sector stability variances. The results indicate that both the level of output growth and banking sector stability have a significant impact on their own variance. Higher output growth is followed by lower output variance in the following quarters (column 3, rows 1). In other words, uncertainty about future output growth is smaller in booms than in recessions.¹¹ In contrast, the variance of banking sector stability increases when the banking sector's distance-to-default is high (column 4, rows 3 and 4). This signifies that uncertainty about future banking sector stability is higher during periods of stability. Combined with the positive autocorrelation for the banking sector described previously, our results imply that an unstable banking sector is more likely to be followed by a further period of instability, than a stable banking sector is to be followed by another period of stability.

Table 1 additionally shows that banking sector stability has a negative and significant impact on output growth variance (column 3, row 3). This means

¹¹ This is in line with the negative link between variance and growth identified by Ramey and Ramey (1995) and Fatás and Mihov (2003).

FIG. 3. IMPULSE-RESPONSE FUNCTION FOR REAL OUTPUT GROWTH AND BANKING SECTOR STABILITY

that a stable banking sector is followed by reduced uncertainty about future output growth. Combined with the positive link between banking sector stability and output growth, our findings indicate that a stable banking sector is more likely to be followed by high output growth, than an unstable banking sector is to be followed by low output growth. Interestingly, we find that higher uncertainty about the stability of the banking sector generally follows higher output growth (column 4, row 2). Combined with the positive link between output growth and banking sector stability, this means that, even though banking sectors are on average more stable after a growth in output, the probability of observing a banking crisis is higher after a period of growth.

Figure 4 documents the behavior of output growth and banking sector stability variances after shocks. The graph shows the difference between the average variance with and without shocks. As explained previously, a positive shock (to either output growth or to banking sector stability) reduces the variance of output growth (left-hand side panels). A positive shock to banking sector stability increases its own variance (right-hand side lower panel). Finally, a shock to output growth increases banking sector stability variance (right-hand side upper panel).

FIG. 4. IMPULSE-RESPONSE FUNCTION FOR REAL OUTPUT GROWTH AND BANKING SECTOR STABILITY VARIANCE

4.1.2 Impact on inflation

Table 2 presents the estimated pVAR with inflation and distance-to-default as endogenous variables with a lag of 2.¹² It shows that neither inflation nor banking sector stability has an impact on the other. The results for the variance equations and for their impulse-response functions (Figure 5) show that higher inflation increases the uncertainty about next period inflation, but decreases the variance of distance-to-default after one period. Impulse-response functions additionally show that the variance of inflation tends to decrease for a very short period after a positive shock to banking sectors degree of stability.

4.2 Non linear impact of the banking sector stability

In the previous section we showed that some empirical evidence of a linear link between banking sector stability and the distribution of output growth exists. However, some authors have suggested that the main impact of banking sector stability on the real economy is non linear. In this section, we briefly

¹²The number of lag is determined by the Akaike Information Criterion.

TABLE 2
 LINEAR IMPACT OF BANKING SECTOR STABILITY ON INFLATION

	Level		Variance	
	$Inflation_t$	DD_t	$\log(\sigma_{Inft_t}^2)$	$\log(\sigma_{DD_t}^2)$
$Inflation_{t-1}$	1.0458**	0.0007	0.0623	0.1427**
$Inflation_{t-2}$	-0.1237**	-0.0080	0.1143*	-0.1910**
DD_{t-1}	-0.0487	0.9765**	0.2286**	0.5770**
DD_{t-2}	0.0330	-0.0254	-0.2172**	0.3480**
Oil_t	0.5015**	-0.0428		
Oil_{t-1}	0.1309*	-0.0097		
Oil_{t-2}	0.3227**	-0.0280		

(**) indicates that the coefficient is significant at the 5% (1%) level. Level: estimated coefficients of equation (8) with inflation and banking sector's distance-to-default as endogenous variables and oil price yield as exogenous variable. Variance: estimated coefficients for equation (12) with inflation and banking sector's distance-to-default as independent variables.

FIG. 5. IMPULSE-RESPONSE FUNCTION FOR INFLATION AND BANKING SECTOR STABILITY VARIANCE

investigate this possibility with a simple model.

Concretely, we check whether there is an asymmetric reaction of real output growth and inflation to banking sector stability. Essentially, we assess whether real output and inflation distributions are different in periods following different state of banking sector stability. As per section 3, we define three states for

TABLE 3
NON LINEAR IMPACT OF BANKING SECTOR STABILITY ON
REAL OUTPUT GROWTH

	Level		Variance	
	GDP_t	DD_t	$\log(\sigma_{GDP_t}^2)$	$\log(\sigma_{DD_t}^2)$
GDP_{t-1}	0.1969**	4.0539**	-17.0826**	-2.2483
GDP_{t-2}	0.2115**	3.2440**	-8.3040*	7.0877
$D_{1,t-1}$	-0.0019**	-0.6422**	0.1445	-0.3709**
$D_{1,t-2}$	0.0016**	-0.3758**	0.3846**	-1.2010**
$D_{2,t-1}$	0.0008	1.1228**	-0.2373	0.3551**
$D_{2,t-2}$	-0.0004	0.4656**	-0.3045*	0.1747**
Oil_t	0.0007	-0.0209		
Oil_{t-1}	-0.0019**	0.0067		
Oil_{t-2}	-0.0012	0.0214		

(**) indicates that the coefficient is significant at the 5% (1%) level. Level: estimated coefficients of equation (8) with inflation and banking sector's distance-to-default as endogenous variables and oil price yield as exogenous variable. Variance: estimated coefficients for equation (12) with inflation and banking sector's distance-to-default as independent variables.

the banking sector: unstable, stable and very stable. We say that the banking sector is unstable if its (standardized) distance-to-default is in the first 20

Similarly to the linear estimations, we make use of a panel VAR but we replace the lagged distance-to-default of the right-hand side of equation (8) by two dummy variables: $D_{1,t}$, is equal to one when the banking sector is unstable and zero otherwise; and $D_{2,t}$, is equal to one when the banking sector is very stable and zero otherwise.

Table 3 presents the estimated coefficients of the new pVAR. The results for the dummy variables are particularly interesting. They indicate that only unstable banking sectors have a significant (and negative) impact on real output growth. Particularly stable banking sectors have no impact on real output growth. In contrary, both unstable and very stable banking sectors have a significant impact on real output growth variance.

Table 4 presents the estimated coefficients of the non linear pVAR with inflation. The results are less clear than for the output growth, but it seems that unstable banking sector increase slightly inflation (column 1, row 4).

The non linear model provides some interesting insights into the results from the linear model for output growth. They show that the linear links uncovered are predominantly driven by periods of banking sector instability rather than by a smooth and continuous link between banking sector stability and the real economy.

TABLE 4
NON LINEAR IMPACT OF BANKING SECTOR STABILITY ON
INFLATION

	Level		Variance	
	$Inflation_t$	DD_t	$\log(\sigma_{Inft_t}^2)$	$\log(\sigma_{DD_t}^2)$
$Inflation_{t-1}$	1.0497**	-0.0173	0.0654	0.0386
$Inflation_{t-2}$	-0.1259**	0.0043	0.1034	-0.0815
$D_{1,t-1}$	-0.0757	-0.6516**	0.2017	-0.3533**
$D_{1,t-2}$	0.0985*	-0.3387**	-0.0224	-1.0098**
$D_{2,t-1}$	-0.0485	1.1281**	-0.0161	0.2686*
$D_{2,t-2}$	0.0427	0.4536**	0.0456	0.2236
Oil_t	0.5162**	-0.0189		
Oil_{t-1}	0.1336*	0.0421		
Oil_{t-2}	0.3342**	0.0847		

(**) indicates that the coefficient is significant at the 5% (1%) level. Level: estimated coefficients of equation (8) with inflation and banking sector's distance-to-default as endogenous variables and oil price yield as exogenous variable. Variance: estimated coefficients for equation (12) with inflation and banking sector's distance-to-default as independent variables.

4.3 Expanding the set of macroeconomic variables

The model estimated in Section 4.1 is very simplistic since it makes the hypothesis that real output is function of its lags, of banking sector stability and of oil prices only. In reality, several other economic variables have an impact on output growth. In this section, we extend the set of exogenous macroeconomic variables included in the pVAR to capture their influence on real output growth. More precisely, we add consumption growth rate (ΔC_t), short term interest rates ($STIR_t$), money growth rate ($\Delta M2_t$) growth and investments (ΔK_t) in the sample.¹³ We chose to present these results in a separate section and not directly in the main section because the variables that we include are not available for all the countries studied or for the same period. Indeed, after adding these variables, the sample is reduced to 15 countries instead of 18¹⁴ and the number of observation shrinks from 1757 data points to 1052.

Table 5 shows that real output growth and distance-to-default are still function of their own lag. As previously, real output growth is also dependent on banking sector stability. However, and contrary to the results in Section 4.1, banking sector stability does not depend on real output growth anymore. It is still a function of the macroeconomic environment as banking sector stability decrease for higher short term interest rates and higher investments (column

¹³ We chose variables that are likely to influence transitory business cycles of GDP (see e.g. Stock and Watson, 1999) and not long term growth rates (like e.g. human capital, political environment, etc...). The reasons for that is mainly that we are not interested in the long term structural influence of the banking sector on growth but more in the transitory impact of the fluctuation of its stability.

¹⁴ Australia, Greece and Sweden are missing from the initial sample.

TABLE 5
 LINEAR IMPACT OF BANKING SECTOR STABILITY
 ON REAL OUTPUT GROWTH : EXTENDED SAMPLE

	Level		Variance	
	GDP_t	DD_t	$\log(\sigma_{GDP_t}^2)$	$\log(\sigma_{DD_t}^2)$
GDP_{t-1}	0.2313**	2.2489	-12.5079*	-14.8445**
GDP_{t-2}	0.2032**	-0.9067	-9.5655	0.3829
DD_{t-1}	0.0008**	0.8984**	-0.2344**	0.6176**
DD_{t-2}	-0.0008*	-0.0081	-0.0304	0.3826**
Oil_t	0.0011	0.1029*		
Oil_{t-1}	-0.0011	-0.0155		
Oil_{t-2}	-0.0007	0.0074		
$\Delta M2_{t-1}$	0.0136*	0.3182		
$STIR_{t-1}$	-0.0003**	-0.0200**		
ΔC_{t-1}	0.0848*	0.9168		
ΔK_{t-1}	-0.0000**	-0.0000**		

(**) indicates that the coefficient is significant at the 5% (1%) level. Level: estimated coefficients of equation (8) with GDP growth and banking sector's distance-to-default as endogenous variables and oil price yield as exogenous variable. Variance: estimated coefficients for equation (12) with GDP growth and banking sector's distance-to-default as independent variables.

2, rows 9 and 11). Table 5 also shows that real output growth variance is still a negative function of banking sector stability - i.e. uncertainty about real output growth increases with banking sector instability. The introduction of the new variables changes the results for distance-to-default variance: the uncertainty about banking sector stability decreases with higher real output growth.

5 Banking sector stability and central bank forecast errors

The link between banking stability and economic activity is of particular interest to policy makers which base their monetary policy decisions on economic forecasts. Our estimations above highlighted the importance of banking sector stability on output growth, however, they were unable to identify any significant relationship between stability and inflation. We therefore extend our analysis on banking sector stability and GDP growth by assessing whether additional information embedded in our stability index might help to improve output growth forecasts. We base our analysis on the United States since forecast data is publicly available on the Fed website back to 1965¹⁵, up to a five year delay. For comparability with our previous estimations our dataset that consists of quarterly data from 1980 to 2001.

Despite econometric models playing an important role in Fed projections for

¹⁵ <http://www.philadelphiafed.org/econ/forecast/greenbook-data/index.cfm>.

TABLE 6
CORRELATIONS: DISTANCE TO DEFAULT WITH FORE-
CAST ERRORS

	DD(C)	DD(L1)	DD(L2)	DD(L3)	DD(L4)
current	-0.51***	-0.50***	-0.47**	-0.43**	-0.41**
one	-0.43	-0.41	-0.37	-0.34	-0.28
two	-0.38**	-0.34**	-0.30**	-0.29**	-0.23*
three	-0.34*	-0.29**	-0.26**	-0.28**	-0.04***
five	-0.10	-0.37*	-0.39	-0.39	-0.34*
six	-0.39	-0.29	-0.31	-0.29	-0.25
seven	-0.29	-0.31	-0.32*	-0.31	-0.27
eight	-0.29	-0.41	-0.44	-0.44	-0.41*

Note: (**) denotes significance at the 5% (1%) level. Forecast errors are calculated as the difference between actual and predicted GDP growth. On the vertical axis, current, one... refer to the current forecast, the one-period ahead forecast etc. DD(C), DD(L1), DD(L2) denote the current stability, stability with a one period lag, stability with a two period lag.

macroeconomic growth, they serve only as part of an input into the forecast process. Judgement based intervention, incorporating additional information not grasped by the models, additionally play a vital role (see Reifschneider, Stockton, and Wilcox, 1997). It is, however, unclear what information is incorporated and whether such judgment based adjustments to forecasts are efficient, i.e. whether they for example make efficient use of all information contained in banking sector variables. Since economic activity and interest rates affect financial sector risks, and in turn, the financial sector affects the real economy, it is possible that considering the state of the banking sector in a systematic way would improve forecasts. We therefore investigate whether Fed growth forecasts are indeed making use of information contained in our measure of banking sector stability.

We start by computing simple correlations between the current distance to default and the period ahead forecasts. The correlations are presented in Table 6. Correlations between the stability indicator and the forecast errors are significant for current forecasts as well as for two- and three-period ahead forecasts indicating that some degree of association between these two measures exists. Simple correlations, however, make no a priori assumptions as to whether one variable is dependent on the other. We therefore proceed to describe the dependence of forecast errors on the banking sector stability; implicitly assuming that there is a one-way causal effect from the degree of stability to the forecast errors, regardless of whether the path of effect is direct or indirect.

Our results are presented in Table 7. We find that banking sector stability has a positive and significant impact on the two-and three-period ahead Fed forecasts. Since the forecast error is calculated as the difference between the actual value and the forecasted rate, the result indicates that banking sector stability today results in a significant underestimation of GDP growth the

TABLE 7
ESTIMATION: DISTANCE TO DEFAULT AND FED FORECAST ERRORS

<i>Dependent variable:</i>	<i>one-period ahead forecast</i>	<i>two-period ahead forecast</i>	<i>three-period ahead forecast</i>	<i>four-period ahead forecast</i>
LINEAR ESTIMATIONS				
distance to default	0.19	0.18**	0.12**	0.12*
NON LINEAR ESTIMATIONS				
D_1	-0.10	-0.23**	-0.24**	-0.26
D_2	0.21	0.12	0.18	0.28

Note: *(**) denotes significance at the 5% (1%) level. Forecast errors are calculated as the difference between actual and predicted GDP growth. D_1 and D_2 are dummies capturing periods of instability and stability respectively.

subsequent quarters. Essentially, banking sector stability brings more growth than expected. This finding indicates that additional information embedded in our stability index measure has the potential to improve Fed growth forecasts. We additionally experiment with asymmetric effects in this regard, defining periods of instability, stability and high stability as per section 3. The results are presented in the lower panel of Table 7. The results from the non linear estimation further confirm our previous finding that for the two-period (and three-period) ahead forecasts, instability drives the results.

6 Conclusion

In this paper, we explore the relationship between banking sector stability and the subsequent evolution of real output growth and inflation. Capturing the stability of a banking sector by building an index based on banking sector distance to default, we adopt a panel VAR methodology to assess both linear and non linear relationships between our variables of interest. We show that banking sector stability appears to be an important driver of GDP growth. Periods of stability are generally followed by an increase in real output growth, while instability corresponds with subsequent periods of reduced growth. We also show that a stable banking sector reduces real output growth uncertainty. In addition, we explore the possibility of an asymmetric impact of banking sector stability on the real economy. To do this we distinguish between unstable, stable and very stable periods relative to both historical and international average. We find that the relationship is asymmetric in nature, in that it is driven predominantly by periods of instability.

We further extend the analysis to assess whether additional information embedded in our stability index might help to improve central bank growth fore-

casts. Focussing on data from the Fed, we show that output forecast errors are correlated with our stability measure. Our findings indicate that banking sector stability (*instability*) results in a significant underestimation (*overestimation*) of GDP growth in the subsequent quarters. This result is in line with the notion that additional information, embedded in our stability index measure, has the potential to further improve economic forecasts.

Our findings have several important implications for policy makers. First, we show that for a sample of 18 countries, banking sector stability appears to be an important driver of GDP growth in subsequent periods, highlighting the need for greater attention to be paid to banking sector soundness in the implementation of economic policy. In addition, we find that additional information contained in our banking sector measure could help forecasters to reduce forecast errors, highlighting the need for policy makers to consider banking sector measures in their forecast models.

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