Banks' Risk Endogenous to Strategic Management Choices

Delis, Manthos and Hasan, Iftekhar and Tsionas, Efthymios

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Abstract

Use of variability of profits and other accounting-based ratios in order to estimate a firm's risk of insolvency is a well-established concept in management and economics. This paper argues that these measures fail to approximate the true level of risk accurately because managers consider other strategic choices and goals when making risky decisions. Instead, we propose an econometric model that incorporates current and past strategic choices to estimate risk from the profit function. Specifically, we extend the well-established multiplicative error model to allow for the endogeneity of the uncertainty component. We demonstrate the power of the model using a large sample of U.S. banks, and show that our estimates predict the accelerated bank risk that led to the subprime crisis in 2007. Our measure of risk also predicts the probability of bank default both in the period of the default, but also well in advance of this default and before conventional measures of bank risk.

1. Introduction

Estimating the risk of insolvency is a central part of the economics and management sciences. Under decision theory, the risk of firms is modeled from the variation of the probability distribution of gains and losses associated with a particular alternative, or the risk of firms is modeled simply from the variation between revenues and expenses (Markowitz, 1952). However, from a managerial perspective, risk is better viewed as a set of strategic choices that can be managed to meet performance targets (e.g., Oviatt and Bauerschmidt, 1991; Hu, Blettner, and Bettis, 2011; Bromiley and Rau, 2010). Thus, a comprehensive measure of risk must include these strategic choices and targets; that is, risk is endogenous. To the extent that this holds true, the empirical estimation of risk from the variability of a performance measure is biased and inconsistent.

In this paper we propose augmenting the framework of estimating solvency risk from the profit function (e.g., Ruefli, Collins, and Lacugna, 1999; Bromiley and Rau, 2010) with the implications of management theory. Our paper presents two interrelated novelties. The first novelty is that we model risk from the variance component (the so-called scale factor) of the multiplicative error model of Engle and Russell (1998) and Engle (2002) in order to allow the variance to be decomposed and modeled separately from the remainder disturbance. The second novelty is that we allow this *ex post* risk measure to be endogenous to internal firm characteristics, such as intertemporal managerial strategies and choices, and to targets such as profits. Thus, we essentially provide a new instrumental variables multiplicative error model, in which the scale factor is allowed to be endogenous.

To this end, we propose a three-equation system. The first equation follows from the production-economics theory and is a profit function that includes variance as the formal measure of risk, as well as the standard information on firms' input prices and outputs (or output prices) of production over a number of periods. In the second equation, the variance of profits is a function of the vector of variables that reflect the intertemporal strategic choices of managers. In turn, in the third equation, these strategic managerial choices are endogenous to the contemporaneous and lagged profits, to the contemporaneous and lagged variance of profits, and to other variables exogenous to the direct control of managers.

Thus, profits, their variability, and strategic choices are all endogenous, and the model considers information on choices and targets from both the current and previous periods. From this perspective, our framework is more closely related to managerial perspectives of risk, whereby managers' intertemporal strategic choices actively influence outcomes (Shapira, 1994). Furthermore, our method is quite general and is applicable to any firm for which data on targets (profits, in this analysis), input prices, outputs, and variables characterizing managerial strategic choices are available.

Estimation of this system of equations can be carried out using the method of maximum likelihood, but derivation of the likelihood function and the related Jacobian term is a non-trivial exercise due to the endogeneity of the variance component. We provide a solution to this problem, which essentially extends the multiplicative error model of Engle and Russell (1998) by allowing the variance part of the disturbance to be a function of other decision variables.

We provide insights on the validity of our proposed method using data from the U.S. banking sector over the period 1986q1–2010q2. We assume that the strategic choice of bank managers is to assume risk as a means to increase profits, but also that they consider in their risk decision the levels of capital and liquidity, the share of total loans, and the structure of different types of loans in the current and previous periods. We name these measures the strategic choice variables of bank managers. In turn, we posit that the strategic choice variables are also endogenous to profits, their variability in the current and previous periods, and to other bank-level, structural, and macroeconomic conditions. This is because there are optimal levels of capital, liquidity, loan ratios, and loan structure. For example, holding too much capital is costly because of lower returns on equity. Phrased differently, bank managers endogenously determine profits, risk, and their choice variables in a strategic fashion that considers current and previous choices on the levels of all of these variables.

Our analysis yields quarterly risk estimates for banks. The results indicate that the risk of the average bank was relatively stable up to 2001 and then gradually increased by more than 200%. In this sense, our model fares very well with expectations and detects the buildup of bank risk far before the financial turmoil of 2007. Furthermore, using a series of probit models we show that our bank risk estimates prove to be a good predictor of bank default, as they clearly reflect the higher risk undertaken by banks that became insolvent after the crisis (from 2007 onward). Thus, our model proves to be a good *ex ante* measure of bank risk and a good predictor of the subprime crisis of 2007 and of individual bank default probabilities.

All of our strategic choice variables are important factors in determining the variability of profits. We formally show that a simple model in which the variance of profits is exogenous does not capture the dynamics of risk for individual banks and is not such a good predictor of the risk buildup in the period 2001-2007. Also, simple accounting-based measures that are popular in empirical studies completely fail to capture the increasing trend of bank risk after 2001.

Our paper is naturally motivated by an extensive strategic-management literature on the use of the variance of returns or profits as a measure of risk. Ruefli (1990), for example, convincingly argues that the simple variance of returns does not take into account the contemporaneous performance of the industry, and suggests using managers' perceptions of risk in their firms and industry. Miller (1998) and Miller and Reuer (1996) review and test many of these traditional measures of risk and show similarities and differences between the variance and downside variance of returns. They are also perhaps the first to compare *ex ante* and *ex post* measures of risk. Miller and Leiblein (1996) show the importance of leading and lagging risk and return measures to avoid the mean-variance problem, which Ruefli (1990) also explicitly defines. On this front, Ruefli, Collins, and Lacugna (1999) also highlight the need for risk measures that incorporate managers' *ex ante* decision processes.

Our paper uses the implications of this literature to produce a novel framework in at least three interrelated dimensions. First, our paper incorporates an admittedly non-exhaustive list of bank managers' decision-making processes as elements in the determination of risk. Thus, we provide a new tool in which the strategic management choices are explicitly and efficiently modeled. Given that this is a basic framework, the method can be used to incorporate other industry- and firm-specific managerial choices as determinants of risk. Second, our paper uses lagged strategic-choice variables to avoid the mean-variance problem. Third, our paper provides an *ex post* risk measure (profit variability) that also incorporates *ex ante* strategic choices of bank managers. Thus, our method allows drawing forecasts on the expected default measures from accounting data, which are usually the only data directly available to managers and researchers. We view these three issues/novelties as particularly important for the management literature.

The rest of the paper proceeds as follows. Section 2 presents the empirical model. Section 3 discusses the empirical setup of the econometric model. Section 4 presents the empirical findings. Section 5 concludes.

2. Empirical model

As in the standard production economics and management theory (e.g., Kumbhakar and Lovell, 2000; Elsinger, Lehar, and Summer, 2006), we begin with a profit function of the form:

$$y_{it} = b_1 x_{it} + \sum_{j=0}^{k} b_2 z_{i,t-j} + \sigma_{it} v_{it}, \text{ for } i = 1,\ldots N, \quad (1)$$

where y represents the profit of firm i at time t, x is the standard vector of inputs and outputs in the profit function, z is a vector of endogenous variables included in the profit equation that characterize strategic management choices, σ is the variability of profits, and $v \sim N_{iid}(0, 1)$ is the error term including other unobserved effects.

Following the production theory in economics (Coelli, Rao, O'Donnell, and Battese, 2006; Kumbhakar and Lovell, 2000) and the multiplicative error models of Engle and Russell (1998; 2002), we consider the estimates of profit variability σ as a formal measure of firm risk. Of course, after estimation, one could consider only the downside variance of profits as a measure of risk (Miller and Leiblein, 1996; Belderbos, Tong, and Wu, 2013). Multiplicative error models arise naturally in the context of high frequency data. There are some applications in other areas (Kumbhakar and Tsionas, 2011) where multiplicative error models also arise naturally in low frequency data with equally plausible considerations. Such considerations are not related to the diffusion process, but rather to alternative models of the error term that go back to the literature begun by McElroy (1987). We believe that the application of a multiplicative error model in our context is not so much motivated by considerations of frequency, but rather by considerations of what constitutes a reasonable model. For example, a key issue in our framework is to keep the dependent variable positive. In a nutshell, our framework extends the multiplicative error models to allow for endogeneity of the scale factor (here the variance component), and this contributes to this line of the econometrics literature.

In our setting, the variables in vector z represent managers' strategic choices that jointly determine risk and profits. Also, we use k lags of z in the profit equation (and also in the risk equation 2) to allow profits and their variability to depend on current and past strategic choices. In line with Miller and Leiblein (1996) and Ruefli, Collins, and Lacugna (1999), among others, this allows incorporating the *ex ante* strategic decisions z in an otherwise *ex post* risk measure, and also reduces concerns about mean-variance problems (Ruefli, 1990).

Subsequently, we assume the following additional specification for the variance of the profit function:

$$\sigma_{it}^2 = f(\sum_{j=0}^{k} z_{i,t-j}, \gamma) \qquad (2)$$

where γ is a vector of parameters to be estimated, and $f(z, \gamma)$ is a functional form differentiable in z. The function f can take the form $\sigma_{it}^2 = z'_{i,t-j}\gamma$ or $\sigma_{it}^2 = \exp(z'_{i,t-j}\gamma)$, etc. for all lagged terms of z. In this paper we use both specifications, and because the results are very similar we provide those from the former specification.

Up to this stage, we formally identify risk as the variability of profits from equation (1) and explain this variability in terms of a vector of variables from equation (2). If the variables in z are predetermined or exogenous, estimating equation (1) subject to (2) would be straightforward using the maximum likelihood method. Unfortunately, this is a very strong assumption for most firms because the z represents firm characteristics that are strategically and endogenously determined with the level of risk in the following way:

$$z_{it} = f(\sum_{j=0}^{k} w_{i,t-j}, \sum_{j=0}^{k} y_{i,t-j}, \sum_{j=0}^{k} \sigma^2{}_{i,t-j}). \qquad (3)$$

In equation (3), w is a vector of the explanatory variables of z, which can include x.

A nice feature of the proposed method is that it does not impose more stringent data requirements compared to the usual ones needed to identify the profit function and firms' strategic choices. The econometric estimation of equations (1)–(3) can be carried out using full information maximum likelihood (FIML). However, the formal derivation of the likelihood function and the Jacobian term required for the estimation is a nontrivial exercise because of the endogeneity of σ; we present this derivation in the Appendix. Thus, estimation also requires a new software module, which is written in Gauss and is available on request.

3. Empirical setup for the banking industry

The banking industry is a good example of the importance of the endogeneity of risk in the strategic choices of bank managers (Elsinger, Lehar, and Summer, 2006; Delgado-Garcia, de la Fuente-Sabate, and Quevedo-Puente, 2010). Consider a bank manager who seeks to maximize profits by taking risks with respect to the bank's loan portfolio. To achieve this goal, managers strategically use information on a number of basic bank variables z from the current and the past periods to decide how much risk to take. However, managers also determine those contemporaneous levels of the variables z by using information about the risk and targets (profits) from the current and the previous periods. Ultimately, the main premise of our empirical analysis is that targets (profits), risk, and strategic variables z are endogenously determined.

We construct an unbalanced data set that includes quarterly information for U.S. commercial banks over the period 1986q1–2010q2. We begin by using the complete sample of commercial banks in the Call reports database; then we apply three selection criteria. First, we exclude all observations that have missing data for any of the variables. Second, we exclude outliers in the first and 99th percentiles of the distributions of the respective variables. These are extreme values (outliers) that may influence the results. Third, we exclude any observations for which the output variables are negative (i.e., we use observations for which all outputs are larger or equal to zero). The final sample consists of 814,253 bank-quarter observations.

Our sample encompasses the financial crisis of 2007, which resulted in the largest realization of bank risk since the Great Depression as evidenced by the number of bank failures and the large losses in the market value of banks. Between 2007q4 and 2009q3, the U.S. commercial banking sector has seen an approximately 20% decrease in its total assets, which is by far the largest decrease after World War II. Rajan (2010), among many others, suggests that the seeds of the crisis are to be found in the policies implemented from the late 2001 onward, as a response to the decline in consumer and industrial confidence following the events of 9/11.

A key element of this discussion is that the banking system expanded the supply of credit in the period 2002-2006 by so much that the banking system reached unsustainable levels of risk. For example, Mian, Sufi, and Trebbi (2014) provide evidence that subprime mortgage lenders influenced government policy toward subprime mortgage-credit expansion. Other studies (e.g., Keys, Mukherjee, Seru, and Vig, 2010; Demanyak and Van Hemert, 2011) offer equally supportive evidence for these claims. This being the case, we would expect that the commonly used measures of bank risk, especially the market-based ones, would capture this increase in bank risk-taking. We will show below that these measures fail to do so, while our model provides a good ex ante measure of bank risk with a strong forecasting ability of the subprime crisis.

3.1. Equation (1): The profit function

Following Koetter, Kolari, and Spierdijk (2012) and many others, we use a profit function that models bank profits as a function of bank outputs and input prices in order to estimate equation (1). This is the so-called alternative profit function, which has two important merits compared to the standard profit function (profits being a function of output and input prices). First, it represents a more appropriate specification when market power exists in the output side of the underlying production function (banks remain price-takers in inputs). In practice, banks do exploit some market power (especially in local markets), as they have the ability to differentiate output prices among different customers, geographic areas, and time (Humprey and Pulley, 1997). Second, output quantities are much more accurately measured compared to output prices, which require dividing the aggregate income generated from various activities to the dollar values of these activities. We do, however, examine the sensitivity of our results to the use of the standard profit function.

We provide formal definitions and summary statistics for the variables used to estimate the profit function in Table 1. To define bank outputs and input prices, we follow the intermediation approach (Sealey and Lindley, 1977). Under this approach, a bank's production function uses labor and physical capital to attract deposits, which in turn fund loans and other earning assets. This strategy relates to a large literature on estimating bank efficiency using production functions (e.g., Hughes, Mester, and Moon, 2001). This literature shows that deposits are better modeled as inputs of production. We also experiment with a profit function that additionally includes the dollar value of deposits as an output. The risk measure remains qualitatively similar. Our model's purpose is not to estimate profit efficiency, but bank risk. Thus, we do not split the error term into an efficiency component and a remainder disturbance. However, the aforementioned literature is invaluable in making robust assumptions for our estimation procedure.

Given the above, various categories of loans and other earning assets are used as bank outputs, and relevant ratios of salary expenses, interest expenses, and expenses on fixed assets are input prices. In essence, our approach considers the measurement of on-balance sheet risk. One could also include a disaggregation of securities and noninterest income or off-balance-sheet (OBS) items as outputs. In our case, the results from this exercise (constrained to the post-2001 period due to data availability) are very similar.

[INSERT TABLE 1]

We experiment with both a log-linear and a translog specification for the profit function. Furthermore, we impose linear homogeneity by dividing profits and input prices by *Input price 3* (expenses on fixed assets/total fixed assets). Because *Profits* contains both positive and negative values, taking logs of *Profits* becomes an issue. We solve this problem by imposing y=1 for all y<0 and construct a negative profit indicator variable, say $y1=|y|$, which we use as an additional right-hand-side variable (Bos and Koetter, 2011). However, we also use a specification where we rescale profits to be positive by adding the maximum negative profit in our sample (e.g., Berger and Mester, 1997; Maudos et al., 2002).

3.2. Equation (2): Strategic choice variables z

For the strategic choices z of bank managers, we consider a number of variables but we resort to four main ones. For all variables we include both their current and lagged levels to reflect the fact that managers choose optimally based on information from the current period and the recent past. We set the number of lags in equations (1) and (2) to four because we find that previous lags are statistically insignificant.

The first variable we use is the ratio of equity capital (equity capital to total assets) of banks, which is the most basic measure of bank capitalization (Grier, 2007). The empirical literature on the relation between risk and capital is quite long (Shrieves and Dahl, 1992; Jacques and Nigro, 1997; Aggarwal and Jacques, 2001; Rime, 2001; Jokipii and Milne, 2011). The majority of these studies find a positive relation between capital and risk and attribute it to the unintended effect of minimum capital requirements, regulatory costs, bankruptcy cost avoidance, and managerial risk aversion. These empirical findings are in line with a recent strand of theoretical models suggesting that—under the assumption of risk-averse utility of banks—the bank portfolio composition will become more risky in the presence of higher bank capital (Acharya, 2009).[1] Also, even though bank capital is regulated and thus bank managers do not have full control over it, banks are inclined to hold a level of capital higher than the minimum capital ratio. There are two main reasons behind this choice, namely the regulatory costs for non-compliance and the excess pricing of interbank lending and asset securitization (e.g., VanHoose, 2007).

In turn, liquidity in bank management (usually measured by the ratio of liquid assets to total assets) is needed for two main reasons. The first reason is to satisfy the demand for new loans and the second reason is to meet the daily and seasonal changes in deposits. Liquidity also inspires confidence in the banking firm, but too much liquidity is unwarranted, because liquid assets do not earn interest. Therefore, banks with more liquid assets are generally willing to increase their levels of risk in search for higher yield. Given the above, we expect liquidity to have a positive effect on risk (Freixas and Rochet, 2008). However, the opposite direction should be negative, as banks with higher levels of risk should have a relatively low level of liquidity in their portfolios. Our measure of liquid assets is calculated as the ratio of bond holdings, share holdings, and interbank assets to total assets.

We further assume that bank managers make their strategic risk choices based on the current and past levels of total loans as a share of total assets, as well as the mix of these loans. These variables are essentially measures of the management of loan structure, which has been

[1] An older theoretical literature shows that capital adequacy regulation reduces the total volume of risky assets (Merton, 1977; Sharpe, 1978).

shown to be a major determinant of bank risk in the relevant literature (e.g., Cebenoyan and Strahan, 2004; Hirtle, 2009). We use two proxies for the structure of the loan portfolio.[2]

The first is the simple ratio of total loans to total assets (loan ratio), which is a measure of bank specialization in lending. A low proportion of total loans as a share of total assets indicates a lack of attractive business opportunities and a stress on profits. A very high loan ratio indicates an increased proportion of very risky assets. In general, however, we expect a positive relation between the loan ratio and bank risk, as banks should expand their lending opportunities to raise profits.

Our second measure is a Herfindahl index of the four loan categories that we use as bank outputs, constructed by the summation of the squared share of the different loan categories. We name this variable "loan structure." Banks with a high loan structure specialize in a specific loan category, and this may imply a low level of risk due to a learning-by-doing mechanism. However, a high degree in loan specialization generally implies a low degree of asset diversification, which is a primary reason for bank failures. Not surprisingly, most of the banks that failed after 2007 were relatively small banks with a low degree of asset specialization. Thus, we expect the relation between loan structure and bank risk to be positive.

One can in fact assume that the volatility of bank profits is endogenous to a number of other bank characteristics. Here, we opt for providing a rather simple example of the proposed method without trying to be exhaustive on the strategic choices of bank managers, which can vary with the goals of each research project. However, we firmly believe that the four variables discussed above are important strategic choices of banks, as described in the financial intermediation theory (Freixas and Rochet, 2008).

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[2] The measure suggested by Cebenoyan and Strahan (2004) is related to loan purchases and sales. We cannot use this measure because the relevant information in the Call Reports database ends in 1993.

3.3. Equation (3): Determinants of z

In equation (3) capital, liquidity, the loan ratio, and the loan structure are a function of profits, risk, and a number of variables *w*. Again, we set the number of lags for profits and risk in equation (3) to *k*=4. We run many alternative specifications to choose the variables *w* but resort to including the fourth lag (annual lags) of *Size* (logarithm of real total assets of banks). This is a reasonable assumption in the literature regarding the determinants of bank capital and liquidity (e.g., Freixas and Rochet, 2008; Flannery and Rangan, 2008). In particular, market investors usually follow and scrutinize larger and more efficient banks more closely. Thus, these banks may have better access to wholesale liabilities, loan sale markets, liquid assets, etc. With better access to these liquidity sources, the managers of larger banks may decide to hold less capital and liquidity in order to have a higher loan ratio or specialize less in particular forms of lending compared to small local banks. Alternatively, larger banks have more complex balance sheets and are more closely supervised. Thus, their managers might decide to finance bank activities with a larger proportion of equity capital or maintain a higher portion of liquid assets to meet unexpected demand.

We also use as *w* the first lags of the three-month T-bill rate and the industrial production index as macroeconomic determinants of bank risk that are exogenous to managers' strategic choices (Jimenez, Ongena, Peydro, and Saurina, 2014). These variables enter equation (3) lagged once (values for the previous quarter) to allow information to reach the market. By including these variables, we capture the fact that bank managers shape their risky behavior by observing, *inter alia*, the state of the monetary and macroeconomic environment (Miller, 1998). One can very easily experiment with other variables common to all banks in equation (3) and examine the sensitivity of the results. For example, we experiment with regulatory dummies characterizing major regulatory events and institutional variables. Our main results are unaffected.

4. Empirical results

Table 2 reports estimation results for the variables in equations (2) and (3). We report the results for four specifications. The first two are log-linear specifications, and the last two are translog specifications. Specifications (1) and (3) include only the capital and liquidity variables as *z*, whereas specifications (2) and (4) include all four strategic choice variables discussed in Section 3. We do not report the estimated coefficients from equation (1) and the coefficients on the lagged terms for the variables in equations (2) and (3) because the number of estimated parameters is very large.[3] However, we do note that all the coefficients on the five outputs bear the expected positive sign and are statistically significant at the 1% level, while the coefficient estimates on the input prices are negative and statistically significant at the same level of significance. These results are in line with the standard duality theory, suggesting that expansion of outputs leads to higher profits primarily due to economies of scale, while more expensive inputs raise costs and lower the profitability of firms in general and banks in particular.

In Table 2, all coefficient estimates (except from profits in the liquidity equation) are statistically significant and bear the expected sign. The coefficient estimates on the risk equation (2) are intuitive. The managers of banks with higher levels of capital and liquidity take on higher risk, and the same holds for banks with a high loan ratio and a Herfindahl index of loan structure. These findings are in line with our theoretical priors discussed in Section 3.2 and with the theoretical predictions of the moral hazard theory, which posits that increasing capital

[3] Almost all the lags in equations (1) to (3) are statistically significant at conventional levels and show that bank managers make decisions based on information from both the current period and the recent past (up to four lags).

requirements constitute a means to lower bank managers' perceptions on the risk of default and increase risk-taking (e.g., Jokipii and Milne, 2011; Freixas and Rochet, 2008).

[INSERT TABLE 2]

The relevant coefficients are also economically significant. In column (4), which shows the results from the most demanding model, a one-standard-deviation increase in a bank's equity-capital ratio increases risk in the next period by 0.082. Given that the average risk estimated in column (4) is 0.105, this is a large increase. The economic significance of the liquidity ratio is quite smaller. Perhaps the most important responses in risk come from the variables characterizing the credit-risk management and the loan structure. Specifically, a 10% point increase in the loan structure (e.g., from its mean of 0.17 to 0.27) will increase risk by 0.06 (or from its average of 0.105 to 0.165), which is a very large increase indeed.

The results in the capital, liquidity, loan-ratio, and loan-structure equations are also intuitive. Our risk measure has a positive effect on capital, which implies that as risk increases banks decide to hold more capital to strengthen their safety net in case of adverse developments (Shrieves and Dahl, 1992; Aggarwal and Jacques, 2001; Rime, 2001; VanHoose, 2007; Jokipii and Milne, 2011). In contrast, risk negatively affects liquidity, implying that a higher level of risk-taking will squeeze the risk-free liquidity holdings of banks. As liquidity is reduced the loan ratio usually increases, and thus the opposite result holds in the effect of risk on the loan ratio. In the last panel of Table 2 we find that risk has a positive effect on the loan structure. This result implies that as the level of risk increases, banks tend to specialize in particular forms of lending for which they establish an expertise, which is consistent with the fact that in our sample most of the banks are relatively small (see also Bonfim and Dai, 2012). The three variables that help with the identification of the system of equations, namely the lagged bank size, interest rate and industrial production are all highly statistically significant determinants in equation (3) and irrespective of the variables used as z.[4]

Still, our results that are of main interest are those regarding the variance in profit. In Figure 1, we present densities of the risk estimates (estimates of the variance σ) from the last two specifications (the translog models), which are more flexible. The distributions show a concentration of relatively low values of risk that correspond to the earlier quarters of our sample, and a smaller concentration of relatively high values that correspond to the quarters before and during the banking crisis of 2007.

[INSERT FIGURE 1]

In Figure 2 we present the quarterly average of the observation-specific risk measures. The four lines correspond to the results from the four specifications of Table 2. Irrespective of the functional form, bank risk is fairly stable until 2001 but increases by more than 200% thereafter. This pattern is robust to the inclusion of a time trend also in equation (1) and alternative determinants of z in equation (3). Therefore, all models capture the perceived increase in bank risk that took place after 9/11 and prior to 2007. Furthermore, all models document a tendency of risk to decrease following its peak in 2007–2008.

[INSERT FIGURE 2]

A number of recent studies suggest that certain developments in the financial sector have led to lower informational asymmetries, trigger intensified competition, expand credit, and create incentives for bank managers to search for higher yields via riskier projects. Rajan (2010) states

[4] Of course, we can include the contemporaneous bank size and interest rate as direct determinants of bank risk in equation (2). In fact, there is a large number of other variables that we could include and this is a matter of choice, and assumptions. We find that our system of equations is surprisingly stable to the inclusion of other variables in equation (2), the results being very close to the ones reported in Table 2. Bank size has a positive and statistically significant coefficient on bank risk and the interest rate a negative and significant coefficient. The former result is in line with the very recent work of Laeven, Ratnovski and Tong (2014). The latter result is in line with the literature on the risk-taking channel of monetary policy (e.g., Jimenez, Ongena, Peydro, and Sairina, 2014).

explicitly that the source of such behavior could be an environment of low interest rates and argues that increased political pressure to finance the economy in general and the housing market in particular largely drove increasing bank risk prior to 2007.

Acharya and Naqvi (2012) calculate the ratio of housing prices to rents in the United States over the same period as our study in order to characterize the evolution of asset prices. The evolution of this index, which is one of the very few successful leading indicators of the crisis, is quite similar to our indices in Figure 2. Many other scholars suggest similar mechanisms that increase bank risk; our new measure largely confirms these perception-based arguments and is in line with the very few indicators that successfully predict the financial crisis of 2007.

We identify only one slightly different risk pattern through time among the four specifications. This comes from using a translog specification, as opposed to a log-linear one. The flexibility of the translog profit function seems to capture a stronger decline in the variability of profits after the eruption of the crisis in 2007 (see especially line 4). This seems meaningful because banks lower their exposure to extremely risky assets as soon as possible after the eruption of the crisis, and regulation became more stringent with an increased number of inspection audits and enforcement actions. However, we should note that risk remains quite high as compared to the period before 2001. Given this evidence, we favor the translog specification.

We carry out some additional sensitivity analyses in Table 3 and graphically present the risk estimates in Figure 3. The first column reports the results from the standard profit function as opposed to the alternative profit function. This involves using the output prices (see Table 1 for definitions and summary statistics), as opposed to the output quantities. The results are qualitatively similar to those reported in Table 2, although they create some additional volatility in the average risk indices as shown in Figure 3. This volatility most likely comes from the less accurate measurement of output prices (Humphrey and Pulley, 1997). In turn, the second column reports the results from the rescaling of profits. Again, with small wrinkles, the results are qualitatively similar with those of Table 2 and produce a similar trend in the average levels of risk.

[INSERT TABLE 3]

[INSERT FIGURE 3]

We also estimate a simple model in which the variance is not endogenous to any variable and report the annual trend in the average risk in Figure 4. This is equivalent to the estimation of equation (1) alone and the derivation of the variance of profits therefrom. We find that this specification does capture an increase in bank risk after 2001 and a decrease in 2007. Yet the time pattern of this line is quite different, showing a large increase in 1992. Not coincidentally, Basel I was enacted in 1992. Thus, the differences in the results show the special role of considering the strategic choice variables that are endogenous to banks' managerial models when estimating bank risk. Also, the results from this model reflect some seasonality that is not smoothed by the endogenous decisions of bank managers. Thus, the model in which risk is not endogenous is systematically different and largely fails to estimate risk precisely.

[INSERT FIGURE 4]

The value of our method also proves quite significant when comparing its results with the indices of bank risk that the previous literature favors (e.g., Ioannidis, Pasiouras, and Zopounidis, 2010; Wright, Kroll, Krug, and Pettus, 2007). We use three such measures based on accounting data (Figure 5), namely the ratios of loan-loss provisions to total loans, nonperforming loans to total loans (credit-risk measures), and the *Z-score* = (*ROA* + *EA*)/*σROA*, where *ROA* is the return on assets, *EA* is the ratio of equity capital to total assets, and *σROA* is the variance of *ROA* over a three-year period (12 quarters). The *Z-score* is a textbook measure of the risk of bank default.

These three indices use the same data from the Call reports. We also use a market-based measure of bank risk, namely the three-year CDS rate for rated banks (Figure 6). This measure also shows that it better captures the realized risk and did not forecast the buildup of bank risk prior to 2007.

[INSERT FIGURES 5 & 6]

Evidently, all these measures fail to capture the increase in bank risk or the extent of this increase after 2001 and before 2007. Specifically, the credit-risk measures and the CDS rate increase only after the crisis became apparent well into 2007. The Z-score, even though it provides a more accurate reflection of risk because it includes an element of variance, documents only minor increases in the risk of bank default. We attribute these limitations to the fact that they do not follow standard economic theory (with the exception of the Z-score), they reflect a static picture of accounting data, and they do not account for the endogeneity/simultaneity issue discussed in this paper.

A natural experiment to validate the power of our method is to examine the behavior of banks that at some point are insolvent. Intuitively, the risk of these banks prior to default should be considerably higher than the industry average. In Figure 7, we plot for the period 2001q1–2010q2 the risk of the banks that became insolvent during the period 2007q1–2010q2 (and thus stopped operating or were acquired by other banks). This information is from the FDIC, and we match the data using the bank certification numbers. The risk metric to obtain the failed banks' average risk by quarter is from the estimation of specification (4) of Table 2.

[INSERT FIGURE 7]

The results essentially validate our measure of risk as a proxy for the risk of default. In particular, the risk of banks that became insolvent during the financial crisis that began in 2007 is considerably higher than the industry average, especially after 2004. An interesting finding is that the risk of the failed banks peaks in 2007, which coincides with the official eruption of the crisis. Clearly, this exercise offers considerable evidence that our risk measure provides early warning signals for bank problems. Yet, a rather worrisome finding is that the risk of insolvency, as reflected in our measures, remains quite high in the period 2008–2010. Notably, FDIC data suggests that 294 more banks failed between 2010q1 and 2012q3.

On the same line, we proceed a step further and we examine the extent to which each risk measure explains the probability of bank default. Specifically, we use a series of probit models (11 in total), separately regressing each of the estimate risk measures and the conventional risk measures included in Figures 5 and 6 on a dummy variable that takes the value one at the quarter the bank defaulted and zero otherwise.

Panel A of Table 4 reports the results (marginal effects) when each explanatory variable enters contemporaneously with the date of default. The results show that our risk measures strongly explain the probability of bank default, with Risk4 (the one corresponding to equation 4 of Table 2) explaining 86% of the probability of default. From the rest of the measures, the problem loans explain 84% and the CDS rate (available for a limited number of banks and from 2001 onward) explains 88%. The rest of the variables are inferior, with the Z-index being the worst predictor.

[INSERT TABLE 4]

In Panel B we repeat this exercise, this time lagging all explanatory variables of default by one year. This allows examining whether these variables provide an *ex ante* measure of the risk of default. In this case, our measures clearly outperform the conventional ratio-based measures of bank risk. Specifically, Risk4 still explains 84% of the probability of default, while the explanatory power of problem loans falls to 49%. This exercise provides further evidence that problem-loans based variables are better viewed as ex post measures of bank risk. The predictive power of the rest of the accounting-based measures also falls considerably.

5. Conclusions and implications

Most empirical economics and management studies rely on measures of solvency risk from the variability of target outcomes. This study proposes a new method for estimating firms' risk, the novel feature being that risk, measured from the variance of the profit function, is endogenously determined by targets (here profits) themselves and by certain strategic managerial choices. In doing this, we augment the multiplicative error model of Engle and Russell (1998) by allowing the scale factor (here the variance) to be an endogenous variable, and offer an explicit estimation path using the maximum likelihood method.

By using information on performance targets and choices from both the current and past periods, the proposed empirical framework incorporates part of bank managers' intertemporal choices and injects elements of *ex ante* risk into an otherwise *ex post* measure. Thus, our framework is an effort to bridge part of the gap between estimates of risk emerging from the existing theories and those inherent in managerial perceptions of risk and risk-taking, whereby managers actively influence the outcome.

We show that there is fertile ground for analyzing the risk of U.S. commercial banks over the period 1986q1–2010q2. The results show that failing to account for bank managers' strategic choices as endogenous determinants of risk and profits produces estimates of risk that are largely flawed. Specifically, we show that bank risk marginally increases from 1986 to 2001, but that from 2001 to 2007 the increase is more than 200%. This finding is in line with the perception that since

2001 and prior to the eruption of the financial turmoil of the late 2000s, various economic and political forces shaped an environment in which banks' risk substantially increased.

In contrast, most (if not all) accounting- and market-based ratios that are popular with researchers and policymakers as measures of bank risk fail to show this substantial increase in bank risk from 2001 to 2007. Also, by matching the risk measures from our method with information on banks that failed after 2007 and using a series of probit models, we show that our measure is a good predictor for default risk both at the time of the default and one year ahead, while the accounting-based measures of risk are worse predictors than our measure, especially one year ahead of the default.

Admittedly, we do not attempt to be exhaustive with respect to including all potential managerial choices and performance targets (profits) in a unified framework of firm risk. This would be a non-pragmatic approach for management theory and practice, given that any model of risk requires certain assumptions about the variables that capture the choices and targets. As March and Shapira (1987) note, managers may deny risk, associate risk only with negative outcomes, adopt different descriptions of risk, and even feel that measuring risk by a simple number might not even be desirable.

What we do attempt in this paper, however, is to provide a more flexible tool through which a model of risks and performance targets can incorporate managers' strategic choices. This will then allow researchers and practitioners to indicate the specific choices and performance targets based on their own theoretical considerations and perceptions, as well as the type of firm or industry analyzed and the timing of the study. Thus, an obvious extension of our work is to apply our model to other industries during different time periods (e.g., good periods and crises periods), as well as to other management objectives and strategic choices (see e.g., Bromiley and Rau, 2010;

Delgado-García, de Quevedo-Puente, and Díez-Esteban, 2013). A fruitful and novel exercise would also be to consider elements of public policy as a determinant of risk (e.g., Marquis and Huang, 2009). We leave this and other issues as a *desideratum* for future research.

Appendix. Formal derivation of the econometric model

Let us re-write the system of the equations (1)–(3) as the following general simultaneous equation model (for simplicity we drop the subscripts *t* and *j*):

$$\Gamma z_i = \mathrm{B} x_{i2} + \varphi_1(y_i)\lambda_1 + \varphi_2(\sigma_i^2)\lambda_2 + u_i \,,\ u_i \overset{iid}{\sim} N(0,\Sigma), \qquad (4)$$

Here, φ_1 and φ_2 are known univariate differentiable functions (e.g., $\varphi_j(w) = w$ or $\varphi_j(w) = \log w$, $j = 1,2$), and λ_1 and λ_2 are $G \times 1$ vectors of coefficients. Γ and B are $G \times G$ and $G \times k_2$, respectively, with B representing the matrix of coefficients on the pre-determined variables and Γ representing the matrix of coefficients on the endogenous variables that appear in the system in standard simultaneous equations model notation. Of course, restrictions are assumed in place for Γ and B in view of identification. For example, the diagonal elements of Γ are assumed to be equal to 1 and this matrix must be nonsingular. Moreover, the variance σ_i^2 may depend on x_{i2} and y_i. The Jacobian of transformation from v_i to y_i can be formally computed; this possibility has been recognized before by Rigobon (2003). This is very important because the researcher does not need to identify a set of instrumental variables that are not correlated with v_i; the x_{i1} and x_{i2} themselves are valid instruments.

For simplicity, we can write $\Gamma z_i = \mathrm{B} x_{i2} + \varphi_1(y_i)\lambda_1 + \varphi_2(\sigma_i^2)\lambda_2 + u_i \equiv \mathrm{B}^* x_{i2}^* + u_i$. To begin with, we assume $\lambda_1 = \lambda_2 = 0_{(G\times 1)}$. Then

$$p\left(y_i \mid z_i\right) = \left(2\pi\sigma_i^2\right)^{-1/2} \exp\left[-\frac{\left(y_i - \beta_1' x_{i1} - \beta_2' z_i\right)^2}{2\pi\sigma_i^2}\right] \tag{5}$$

and

$$p\left(z_i\right) = \left(2\pi\right)^{-G/2} \left|\Sigma\right|^{-1/2} \left\|\Gamma\right\| \exp\left[-\tfrac{1}{2}\left(\Gamma z_i - \mathrm{B}^* x_{i2}^*\right)' \Sigma^{-1} \left(\Gamma z_i - \mathrm{B}^* x_{i2}^*\right)\right]. \tag{6}$$

Therefore, the joint distribution of the observed endogenous variables is

$$\begin{aligned} p\left(y_i, z_i\right) &= \left(2\pi\right)^{-(G+1)/2} f\left(z_i;\gamma\right)^{-1/2} \exp\left[-\frac{\left(y_i - \beta_1' x_{i1} - \beta_2' z_i\right)^2}{2\pi f\left(z_i;\gamma\right)}\right] \cdot \left|\Sigma\right|^{-1/2} \cdot \\ &\left\|\Gamma\right\| \cdot \exp\left[-\tfrac{1}{2}\left(\Gamma z_i - \mathrm{B}^* x_{i2}^*\right)' \Sigma^{-1} \left(\Gamma z_i - \mathrm{B}^* x_{i2}^*\right)\right]. \end{aligned} \tag{7}$$

This likelihood function can be maximized using standard numerical techniques. Formal concentration with respect to parameters B^* and Σ is also possible, so the problem can be simplified in terms of maximizing the log-likelihood function of the sample. The details for this exercise are available on request.

In the general case, where $\lambda_1, \lambda_2 \neq 0$, the formulation of $p\left(y_i \mid z_i\right)$ is straightforward, but the formulation of the inverse distribution $p\left(z_i \mid y_i\right)$ or $p\left(z_i\right)$ is not trivial. The Jacobian of transformation is given by

$$D_i = \left\|\frac{\partial\left(v_i, u_i\right)}{\partial\left(y_i, z_i\right)}\right\| = f\left(z_i;\gamma\right)^{-G/2} \left\|\Gamma - \varphi_2' \lambda_2 \frac{\partial f\left(z_i;\gamma\right)}{\partial z_i'} - \varphi_1' \lambda_1 \beta_2'\right\|, \tag{8}$$

after accounting for the fact that the variance is dependent on endogenous variables (the z_i s). If $\sigma_i^2 = z_i'\gamma$, then $\frac{\partial f\left(z_i;\gamma\right)}{\partial z_i'} = \gamma'$. If $\sigma_i^2 = \exp\left(z_i'\gamma\right)$, then $\frac{\partial f\left(z_i;\gamma\right)}{\partial z_i'} = \exp\left(z_i'\gamma\right)\gamma'$.

In this case, we have

$$p\left(y_i, z_i\right) = \left(2\pi\right)^{-(G+1)/2} f\left(z_i;\gamma\right)^{-G/2} \exp\left[-\frac{\left(y_i - \beta_1' x_{i1} - \beta_2' z_i\right)^2}{2\pi f\left(z_i;\gamma\right)}\right] \cdot$$

$$\left|\Sigma\right|^{-1/2} \cdot \left\| \Gamma - \varphi_2' \lambda_2 \frac{\partial f\left(z_i;\gamma\right)}{\partial z_i'} - \varphi_1' \lambda_1 \beta_2' \right\| \cdot \exp\left[-\tfrac{1}{2}\left(\Gamma z_i - \mathrm{B}^* x_{i2}^*\right)' \Sigma^{-1} \left(\Gamma z_i - \mathrm{B}^* x_{i2}^*\right)\right]. \tag{9}$$

The simplest case is when $\varphi_1\left(w\right) = \varphi_2\left(w\right) = w$ and $f\left(z_i;\gamma\right) = z_i'\gamma$. In this case the Jacobian term is simply $\left\|\Gamma - \lambda_2\gamma' - \lambda_1\beta_2'\right\|$, where $\lambda_2\gamma'$ and $\lambda_1\beta_2'$ are rank-one $G \times G$ matrices. Of course, if λ_1 or λ_2 (or possibly both) are zero, further simplifications arise. The typical case is to have profits, y_i, and the variance, σ_i^2, appearing as determinants of the z_is. This may be partly because not all banks have positive profits; therefore, we cannot consider the log of y_i. However, one may have $\varphi_2\left(w\right) = \log w$, with $\varphi_2'\left(w\right) = w^{-1}$. In that case, the Jacobian would be

$$D_i = \left\| \Gamma - f\left(z_i;\gamma\right)^{-1} \lambda_2 \frac{\partial f\left(z_i;\gamma\right)}{\partial z_i'} - \lambda_1\beta_2' \right\|. \tag{10}$$

In terms of our model, it is instructive to provide a simple econometric example to show that risk can also be a function of profits (y_i). Indeed, consider for simplicity the following "mean-scale" model $y_i = \mu + \sigma\left(y_i\right)v_i$, where $v_i \overset{iid}{\sim} N\left(0,1\right)$. Apparently, the Jacobian of transformation is

$$\left|\frac{\partial v}{\partial y}\right| = \left|\frac{\sigma\left(y\right) - \sigma'\left(y\right)\left(y-\mu\right)}{\sigma\left(y\right)^2}\right|, \tag{11}$$

and the density of *y* would be

$$p\left(y\right) = \left(2\pi\right)^{-1/2} \exp\left[-\frac{\left(y-\mu\right)^2}{2\sigma\left(y\right)^2}\right] \cdot \left|\frac{\sigma\left(y\right) - \sigma'\left(y\right)\left(y-\mu\right)}{\sigma\left(y\right)^2}\right|. \tag{12}$$

The Jacobian is nonzero, provided $\sigma(y)$ is not a solution of the difference equation $\sigma(y)-\sigma'(y)(y-\mu)=0$, that is, $\sigma(y)^2$ should not be equal to $C(y-\mu)^2$, where C is a constant. Other specifications for the variance term would be acceptable, for example, $\sigma(y)^2 = C_1 + C_2(y-\mu)^2$, $C_1 > 0$. This shows that, in terms of our model, risk can be a function of profits y themselves, despite the fact that profits are also determined by risk. In that sense, we allow for joint determination of risk and profits.

Note that this is different from a GARCH-M type model, where the lagged variance typically enters into the mean equation. Here the current variance can also enter the mean equation, provided that a proper adjustment for the Jacobian term is made. This point seems to be unpublished, at least to our knowledge.

Suppose, indeed, $\sigma_i^2 = z_i'\gamma + \alpha y_i$. Then, relative to (11), the only difference is that the Jacobian term is $\left\|\Gamma - \varphi_2'\lambda_2\gamma' - (\varphi_1'\lambda_1 + \alpha\varphi_2'\lambda_2)\beta_2'\right\|$. If $\lambda_2 = 0$, the new formulation does not add anything to the Jacobian, otherwise, the contribution depends on $\alpha = \dfrac{\partial f(z_i, y_i; \gamma)}{\partial y_i}$.

A process for the variance as discussed above is perhaps enough for practical purposes. However, one may want to explore the implications of stochastic risk or stochastic volatility for the profit function. Suppose we have a stochastic risk process of the form $\log\sigma_i^2 = \gamma' z_i + \xi_i$, where the new error term is $\xi_i \overset{iid}{\sim} N(0, \sigma_\xi^2)$. Here, we explicitly assume $\log f(z_i, \gamma) = \gamma z_i'$. The full model can now be written as follows:

$$y_i = \beta_1' x_{i1} + \beta_2' z_i + \sigma_i v_i,$$

$$\Gamma z_i = \mathrm{B} x_{i2} + \varphi_1(y_i)\lambda_1 + \varphi_2(\sigma_i^2)\lambda_2 + u_i, \tag{13}$$

$$\log \sigma_i^2 = \gamma' z_i + \xi_i .$$

In that form, we can formally consider volatility, $\log \sigma_i^2$, as an endogenous (but latent) variable. Therefore,

$$p\left(y_i, z_i, \log \sigma_i^2\right) = p\left(v_i, u_i, \xi_i\right) \cdot \left\| \frac{\partial\left(v_i, u_i, \xi_i\right)}{\partial\left(y_i, z_i, \log \sigma_i^2\right)} \right\|. \tag{14}$$

After computing the Jacobian term, the joint distribution is as follows:

$$\begin{aligned} p\left(y_i, z_i, \log \sigma_i^2\right) &= (2\pi)^{-(G+2)/2} \left(\sigma_\xi^2\right)^{-1/2} \left(\sigma_i^2\right)^{-G/2} \cdot \left\| \Gamma - \varphi_1' \lambda_1 \beta_2' - \gamma \left(\varphi_2' \lambda_2' \sigma_i^2 + 2 e_i \varphi_1' \lambda_1'\right) \right\| \cdot |\Sigma|^{-1/2} \cdot \\ &\exp\left[-\frac{\left(y_i - \beta_1' x_{i1} - \beta_2' z_i\right)^2}{2\pi\sigma_i^2} \right] \cdot \exp\left[-\tfrac{1}{2} \left(\Gamma z_i - \mathrm{B}^* x_{i2}^*\right)' \Sigma^{-1} \left(\Gamma z_i - \mathrm{B}^* x_{i2}^*\right) \right] \cdot \\ &\exp\left[-\frac{\left(\log \sigma_i^2 - \gamma' z_i\right)^2}{2\sigma_\xi^2} \right] \end{aligned} \tag{15}$$

where $e_i = \sigma_i^{-1}\left(y_i - \beta_1' x_{i1} - \beta_2' z_i\right)$. The simplest case is to have $\varphi_2' = 1$, so that the Jacobian is independent of σ_i^2. But still the density of the observables is

$$p\left(y_i, z_i\right) = \int p\left(y_i, z_i, \log \sigma_i^2\right) d\sigma_i^2, \tag{16}$$

which cannot be computed analytically. Of course, if $\varphi_2' \neq 1$, the integral is even more complicated and standard simulation techniques proposed in the aforementioned literature need considerable modification. A relatively simple case is when $\lambda_1 = \lambda_2 = 0$. In fact, the critical issue is whether $\lambda_2 = 0$. If not, then stochastic risk appears in the Jacobian terms of the sample likelihood, and formal or numerical integration is troublesome.

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Table 1. Definitions of variables and summary statistics

Variable	Measure	Mean	Std. dev.	Min.	Max.
Profits	Total profits before tax ($US)	5,395.9	121,227.6	-1.81e+07	2.30e+07
Output 1	Commercial and industrial loans ($US)	70,340.8	1,143,058	0	1.42e+08
Output 2	Loans to individuals ($US)	42,828.3	761,145.9	0	9.43e+07
Output 3	Loans secured by real estate ($US)	178,448.6	3,168,042	0	4.75e+08
Output 4	Other loans ($US)	33,906.3	798,096.5	0	8.88e+07
Output 5	Other earning assets ($US)	276,058.4	6,714,982	0	1.07e+09
Output 6	Off-balance sheet items ($US)	232,545	120,222.6	0	6.07e+08
Output price 1	Income from output 1/ output 1	0.053	0.124	0.0010	0.943
Output price 2	Income from output 2/ output 2	0.060	0.142	0.0010	0.816
Output price 3	Income from output 3/ output 3	0.045	0.101	0.0010	0.748
Output price 4	Income from output 4/ output 4	0.058	0.113	0.0010	0.824
Output price 5	Income from output 5/ output 5	0.069	0.157	0.0010	0.913
Output price 6	Income from output 6/ output 6	0.065	0.144	0.0010	0.822
Input price 1	Salary expenses/ total assets	0.0099	0.0053	0.0017	0.0325
Input price 2	Interest expenses/ total deposits	0.0248	0.0147	0.0028	0.0733
Input price 3	Expenses on fixed assets/ total fixed assets	0.0027	0.0018	0.0002	0.0119
Capital	Equity capital/ total assets	0.0960	0.0298	0.0321	0.4600
Liquidity	Liquid assets/ total assets	0.0590	0.0446	0.0021	0.4055
Loan ratio	Total loans/ total assets	0.5848	0.1509	0.0059	0.9230
Loan structure	Herfindahl index of different loan categories	0.1748	0.1152	0.0001	0.9942
Size	Bank size: natural logarithm of total assets	11.289	1.298	8.501	21.293
Interest rate	3-month T-bill rate (in %)	4.543	2.058	0.070	8.533
Industrial production	US industrial production index	75.525	14.622	54.706	100.44

Notes: Profits, the output variables, and size are in real terms.

Table 2. Main estimation results for the system of equations (1)-(3)

Equation:	(1)	(2)	(3)	(4)
Functional form:	Log-linear	Log-linear	Translog	Translog
Eq. (2): σ^2 equation				
Capital	0.171***	0.102***	0.084***	0.082***
	(4.77)	(3.27)	(3.15)	(3.11)
Liquidity	0.084***	0.070***	0.063***	0.016***
	(5.31)	(4.12)	(3.80)	(14.61)
Loan ratio		0.144***		0.120***
		(16.53)		(11.55)
Loan structure		0.790***		0.602***
		(46.77)		(15.11)
Eq. (3): Capital equation				
Profits (y)	0.005***	0.005***	0.004***	0.004***
	(25.38)	(24.42)	(15.15)	(13.28)
Risk (σ^2)	0.004***	0.003***	0.002***	0.002***
	(8.71)	(5.34)	(3.29)	(3.41)
Size $_{t-4}$	-0.011***	-0.011***	-0.009***	-0.009***
	(-12.41)	(-11.68)	(-7.42)	(-7.01)
Interest rate $_{t-1}$	-0.082***	-0.085***	-0.067***	-0.062***
	(-8.69)	(-8.45)	(-5.50)	(-5.48)
Industrial production $_{t-1}$	0.050***	0.048***	0.033***	0.032***
	(13.46)	(12.05)	(7.81)	(7.52)
Eq. (3): Liquidity equation				
Profits (y)	0.003***	0.003***	0.003***	0.003***
	(46.92)	(45.60)	(39.10)	(40.92)
Risk (σ^2)	-0.002***	-0.002***	-0.002***	-0.002***
	(-4.40)	(-4.33)	(-4.01)	(-3.93)
Size $_{t-4}$	-0.001***	-0.001***	-0.001***	-0.001***
	(-7.25)	(-7.10)	(-6.11)	(-5.15)
Interest rate $_{t-1}$	0.001***	0.001***	0.001***	0.001***
	(3.81)	(3.48)	(3.22)	(3.31)
Industrial production $_{t-1}$	0.001***	0.001***	0.001***	0.001***
	(4.11)	(4.14)	(3.19)	(3.36)
Eq. (3): Loan ratio equation				
Profits (y)		-0.000		0.000
		(-0.10)		(0.43)
Risk (σ^2)		0.010***		0.008***
		(57.76)		(30.24)
Size $_{t-4}$		0.022***		0.012***
		(65.63)		(10.33)
Interest rate $_{t-1}$		0.001***		0.001***
		(6.98)		(3.83)
Industrial production $_{t-1}$		0.003***		0.002***
		(7.98)		(4.07)
Eq. (3): Loan structure equation				
Profits (y)		0.002***		0.002***
		(4.85)		(3.22)
Risk (σ^2)		0.011***		0.009***
		(9.40)		(7.62)
Size $_{t-4}$		0.034***		0.017***
		(23.71)		(9.25)
Interest rate $_{t-1}$		-0.001***		-0.001***
		(-13.54)		(-10.48)
Industrial production $_{t-1}$		0.003***		0.002***
		(14.99)		(7.32)

Notes: The table reports estimation results (coefficients and t-statistics) for equations (2) and (3) obtained from the joint estimation of equations (1)–(3), using FIML. We have 814,253 bank-quarter observations, covering the period 1986q1–2010q2. The variables are defined in Table 1. The *, **, and *** marks denote statistical significance at the 10, 5, and 1% level, respectively.

Table 3. Sensitivity analysis: Using the standard profit function and imposing positive profits

	(1) Standard profit function	(2) Imposing positive profits
Eq. (2): σ^2 equation		
Capital	0.163***	0.201***
	(4.04)	(5.61)
Liquidity	0.088***	0.047**
	(5.10)	(2.38)
Loan ratio	0.092***	0.102***
	(7.42)	(9.50)
Loan structure	0.805***	0.605***
	(39.93)	(30.27)
Eq. (3): Capital equation		
Profits (y)	0.007***	0.005***
	(33.34)	(20.04)
Risk (σ^2)	0.003***	0.003***
	(6.01)	(5.82)
Size $_{t-4}$	-0.009***	-0.009***
	(-4.82)	(-5.27)
Interest rate $_{t-1}$	-0.090***	-0.063***
	(-8.15)	(-4.88)
Industrial production $_{t-1}$	0.057***	0.051***
	(15.22)	(11.70)
Eq. (3): Liquidity equation		
Profits (y)	0.002***	0.003***
	(18.66)	(41.27)
Risk (σ^2)	-0.001**	-0.002***
	(-2.30)	(-5.29)
Size $_{t-4}$	-0.001***	-0.001***
	(-6.17)	(-7.58)
Interest rate $_{t-1}$	0.001***	0.002***
	(3.63)	(5.16)
Industrial production $_{t-1}$	0.001***	0.001***
	(4.03)	(4.93)
Eq. (3): Loan ratio equation		
Profits (y)	0.000	0.002**
	(0.94)	(2.15)
Risk (σ^2)	0.008***	0.011***
	(20.15)	(62.13)
Size $_{t-4}$	0.015***	0.019***
	(23.16)	(57.12)
Interest rate $_{t-1}$	0.001***	0.001***
	(4.50)	(6.05)
Industrial production $_{t-1}$	0.002***	0.004***
	(3.27)	(9.23)
Eq. (3): Loan structure equation		
Profits (y)	0.001**	0.002***
	(2.41)	(4.67)
Risk (σ^2)	0.009***	0.011***
	(6.52)	(10.02)
Size $_{t-4}$	0.021***	0.030***
	(8.35)	(18.11)
Interest rate $_{t-1}$	-0.002***	-0.001***
	(-8.57)	(-15.29)
Industrial production $_{t-1}$	0.002***	0.004***
	(5.85)	(16.97)

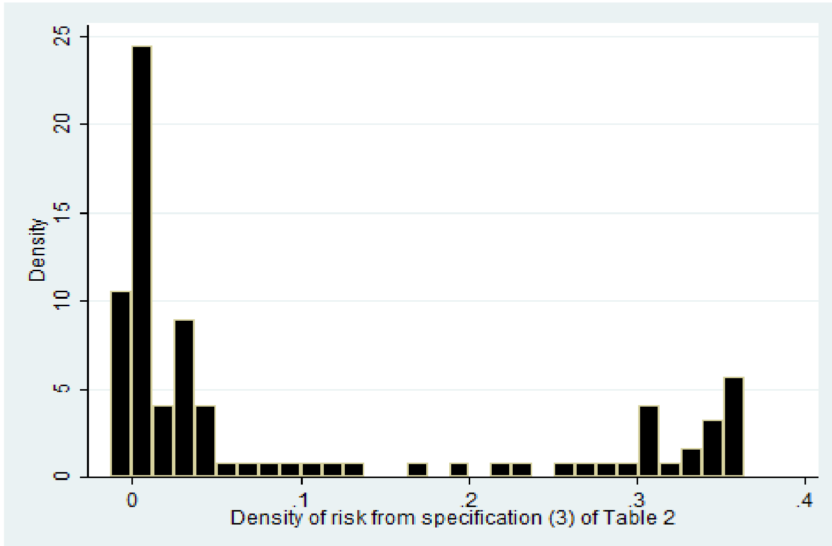
Notes: The table reports estimation results (coefficients and t-statistics) for equations (2) and (3) obtained from the joint estimation of equations (1)–(3), using FIML and the translog specification. We have 814,253 bank-quarter observations, covering the period 1986q1–2010q2. The variables are defined in Table 1. The *, **, and *** marks denote statistical significance at the 10, 5, and 1% level, respectively.

Table 4. Probability of risk measures explaining bank default

	(1) Risk1	(2) Risk2	(3) Risk3	(4) Risk4	(5) Risk5	(6) Risk6	(7) Risk no z	(8) Z-index	(9) Prov.	(10) Pr. loans	(11) CDS
Panel A: Predictions at the time of the default											
Risk	0.666	0.785	0.856	0.861	0.842	0.819	0.632	0.358	0.565	0.837	0.881
	(95.04)	(95.01)	(88.97)	(89.87)	(88.50)	(87.20)	(50.32)	(32.48)	(31.48)	(87.10)	(110.22)
Panel B: Predictions one year before the default											
Risk	0.628	0.732	0.828	0.840	0.810	0.790	0.529	0.207	0.322	0.487	0.693
	(87.03)	(88.48)	(87.55)	(86.38)	(81.59)	(79.20)	(39.16)	(10.20)	(28.35)	(52.15)	(73.81)

Notes: The table presents marginal effects and t-statistics (in parentheses) from the probit regressions between bank default and the six indices of bank risk from the specifications of Tables 2 and 3 (named Risk1 to Risk6), the index of bank risk with no strategic choice variables z, the accounting ratios presented in Figure 5, and the CDS rate. For the latter only a limited number of banks for the period after 2001q1 is used due to data availability. Panel A reports the results for the risk variables at the time of the bank default and Panel B when the risk variables are lagged one year. All marginal effects are statistically significant at the 1% level.

Figure 1. Densities of bank risk estimates



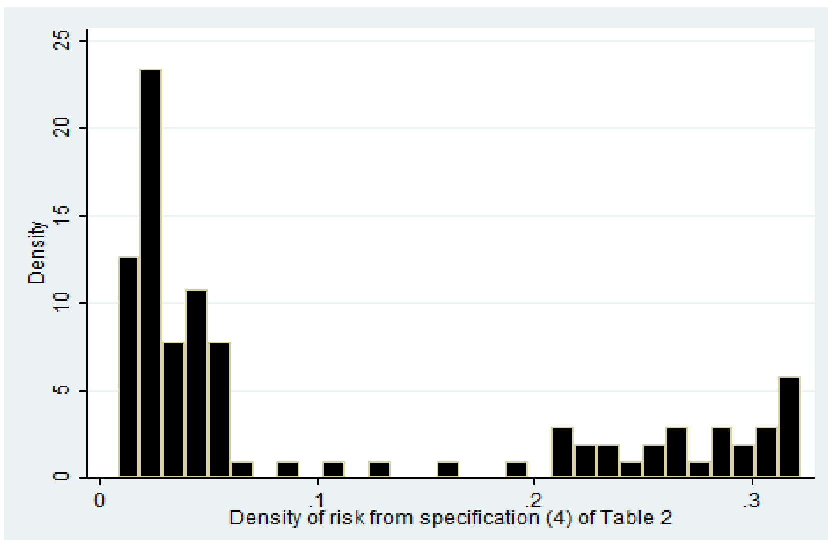


Figure 2. Quarterly average of bank risk from specifications (1) to (4) of Table 2

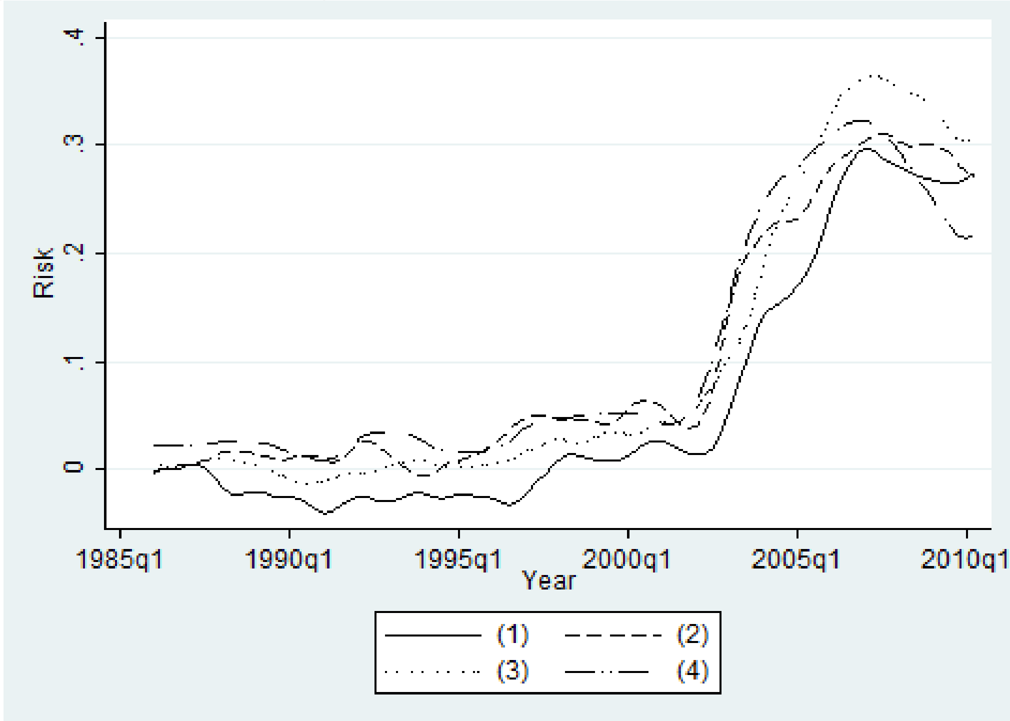
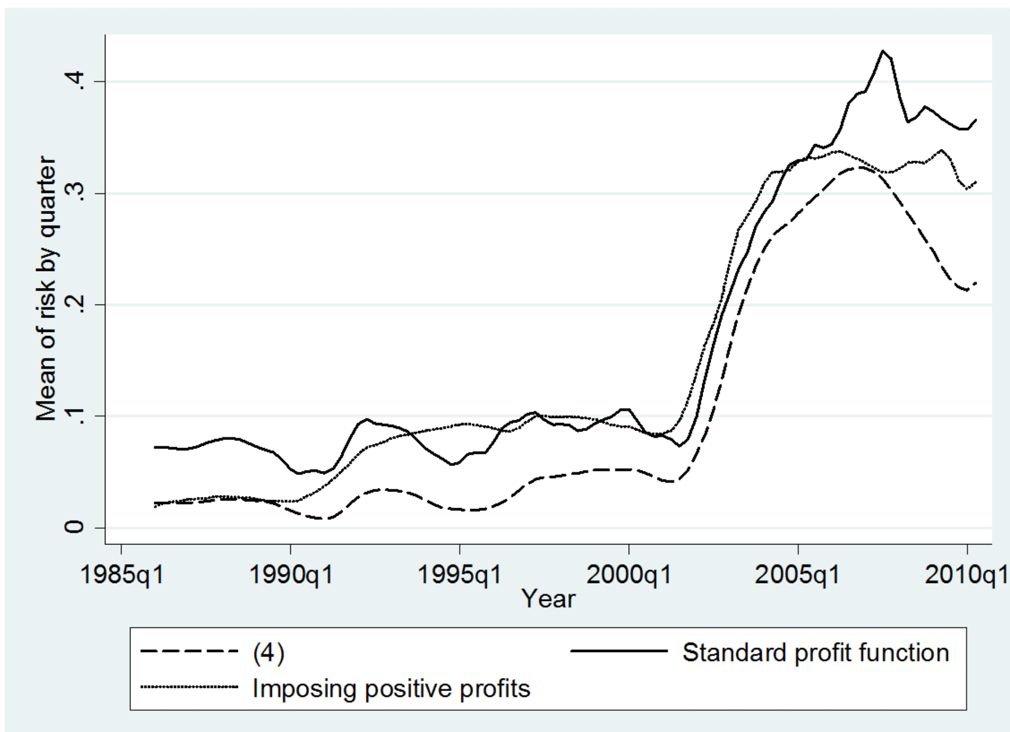
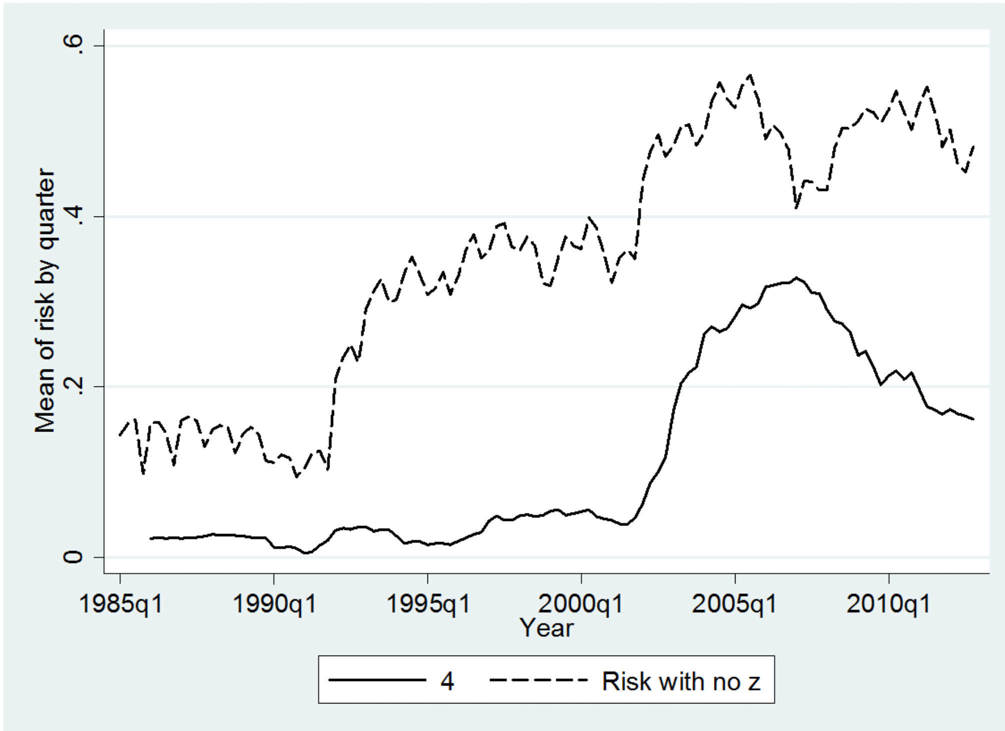


Figure 3. Quarterly average of bank risk from specifications (1) and (2) of Table 3



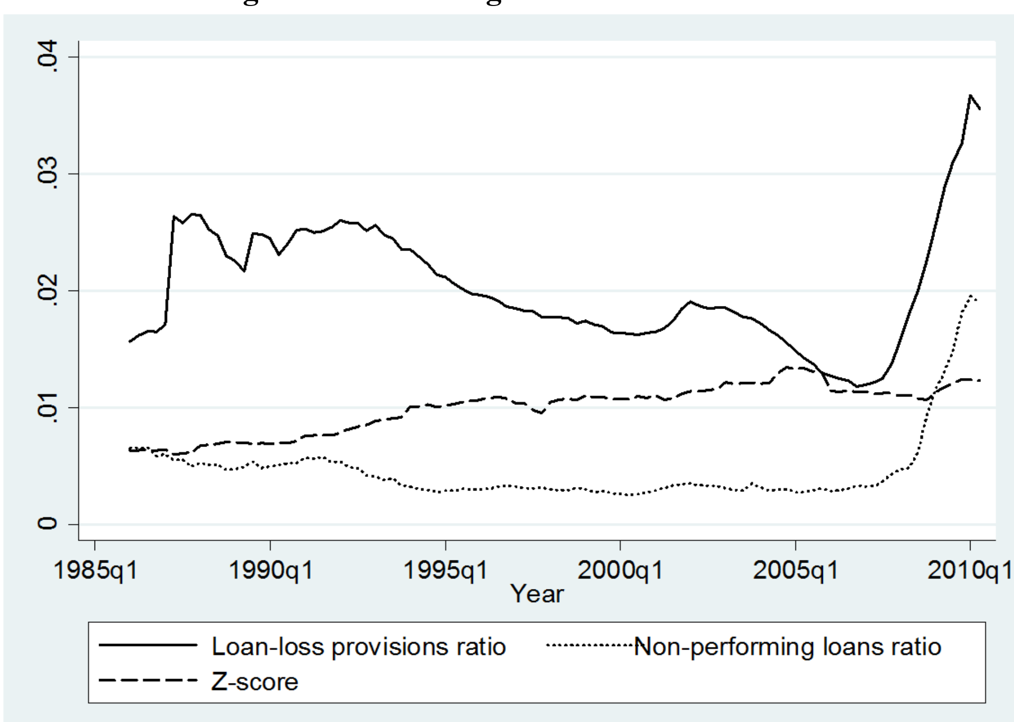
Notes: The figure presents the quarterly average of bank risk from specifications (1) and (2) of Table 3 vs. the equivalent from the specification (4) of Table (2).

Figure 4. Risk of banks without an endogenous variable z compared to the risk estimated from the full sample of banks



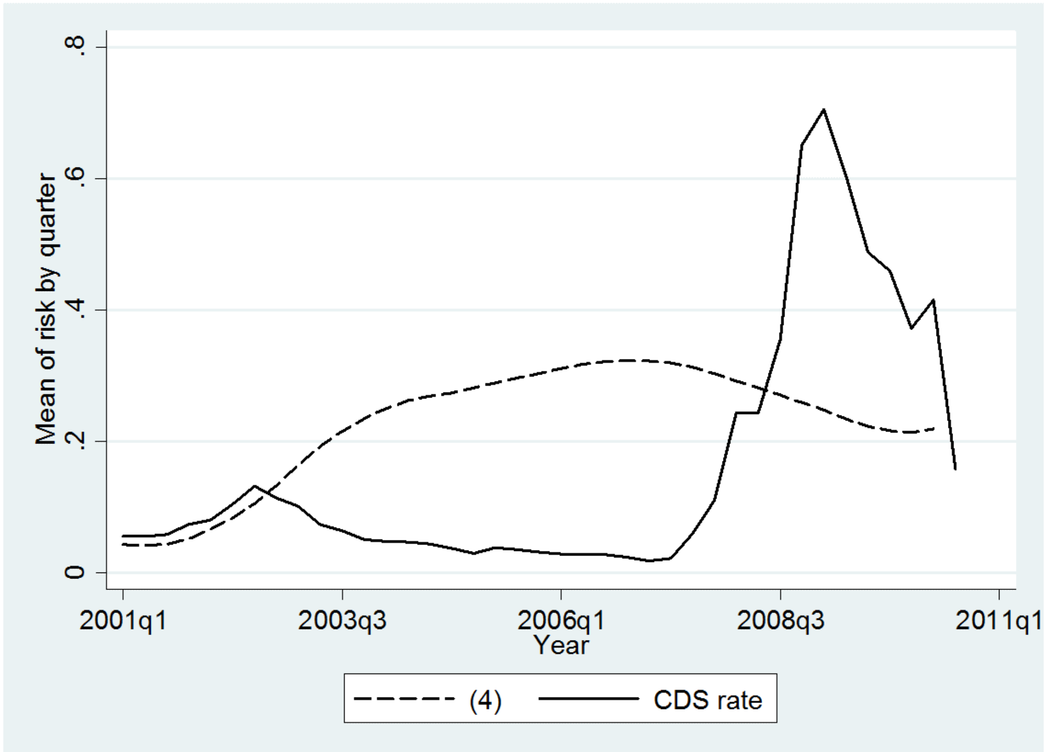
Notes: The figure presents the quarterly average of bank risk from the specification where there are no variables z (equivalent to the estimation of equation (1) alone vs. the equivalent from the specification (4) of Table 2.

Figure 5. Accounting measures of bank risk



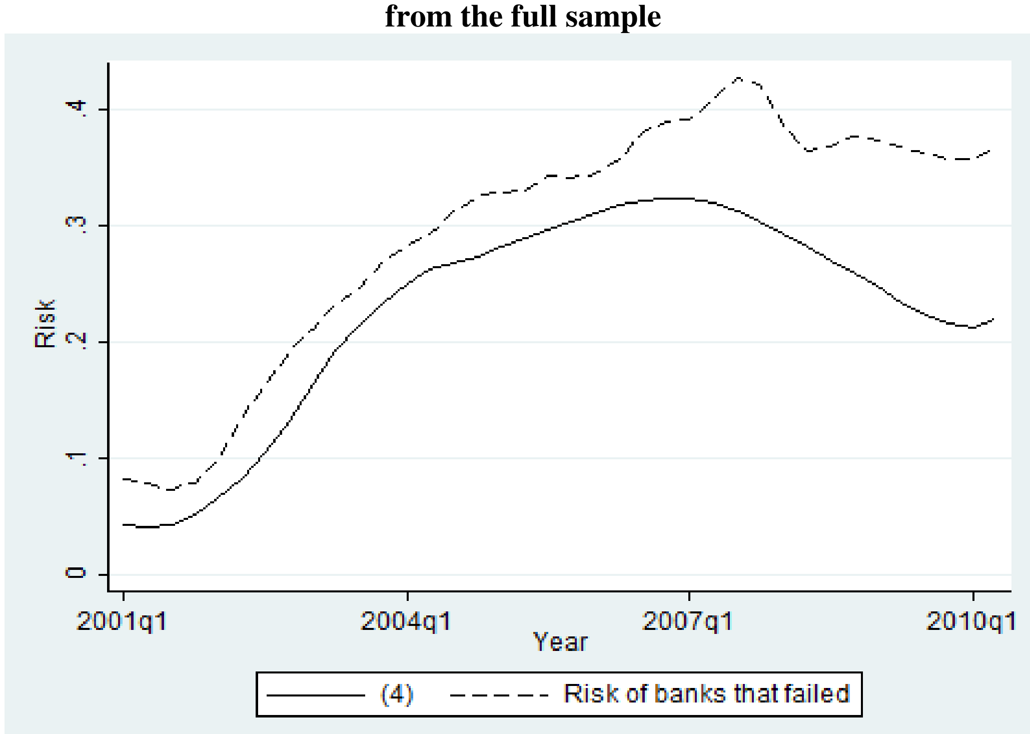
Notes: For the lines in Figure 5, the industry average is (total industry loan loss provisions at quarter t)/(total industry loans at quarter t). The same definition applies to all three lines in this figure.

Figure 6. CDS rate (3-year) compared to the risk estimated from the full sample of banks



Notes: The figure presents the quarterly average of the CDS rate vs. the equivalent from the specification (4) of Table 2.

Figure 7. Estimated risk for banks that failed compared to the risk estimated from the full sample



Notes: The figure presents the quarterly average of the bank-quarter risk values from specification (4) of Table 2 for the banks that failed from 2007 onward (dashed line) relative to all the banks in the sample (solid line).