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Modelling and measuring business risk and the resiliency of retail banks

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Abstract

The paper uses recent developments of the methodology of efficiency frontiers to provide an original modeling of the risk of volatility of banking profits which relies on the estimation of a profit frontier. This methodology allows taking into account coordinated adjustments of banks' costs to revenues as well as the absence of such adjustments. The study uses data of more than ninety French institutions running a retail banking business model over the period 1993 to 2012. Results confirm the resiliency of retail banks in crisis period. The decrease in profitability seems largely sustainable even if case of severe shocks. Thus, in case of a large drop in the banks' lending activity, profit decreases moderately if costs are adjusted quickly, more largely if they are not. A shock on the provision of liquidity services shows less significant effects. In case where banks cannot adjust operating costs, only a very strong shock precipitating banks in the situation of the 5% less profitable could destroy completely yearly profits.

Keywords: Bank solvency, Retail Banking, Business Risk, Efficiency Frontier Methodology, Profit Function.
JEL Codes: G21, D24

Résumé

L'étude exploite les développements récents de la méthodologie des frontières d'efficience pour proposer une modélisation originale du risque de volatilité des profits bancaires reposant sur l'estimation d'une fonction de profit bancaire. Cette méthodologie permet de prendre en compte des ajustements coordonnés des coûts aux revenus aussi bien que l'absence de tels ajustements. Sur la période 1993-2012 et plus de quatre-vingt dix établissements français dans le domaine de la banque de détail, les résultats apportent une confirmation de la solidité de ces banques en situation de crise. La chute de la profitabilité apparaît largement soutenable au regard de la sévérité des chocs considérés dans l'étude. Ainsi, en cas de choc sévère sur l'activité de crédit, le profit chute modérément si les coûts sont ajustés rapidement, plus nettement s'ils ne peuvent l'être. Un choc sur la création de services de liquidité a des effets un peu moins marqués. En cas d'impossibilité d'ajuster les coûts opératoires, il faudrait en réalité un choc très marqué précipitant toutes les banques sans exception dans la frange des 5% les moins rentables pour réduire le profit de l'année à néant.

Mots clés: Solvabilité bancaire, Banque de détail, Risque d'activité, Méthode des frontières d'efficience, Fonction de profit.
Codes JE : G21, D24

Résumé non technique

Lors de la crise de 2008-2009, des activités entières des banques ont été fortement ralenties voire stoppées. Ce fut le cas bien sûr des activités de titrisation, mais aussi de fusions-acquisitions ou de syndication. De tels événements sont à l'origine d'un risque non financier sur les business models des banques, le risque de business. Nous définissons ce risque comme un risque de volatilité des profits des banques. En cas de chocs résultant de l'incertitude de la demande pour leurs produits, les revenus et les marges des banques ne sont pas nécessairement modifiés de la même manière que leurs coûts. Ce risque se distingue des risques financiers que sont les risques de crédit ou de marché. Il se distingue également d'un autre risque non financier, le risque opérationnel. La crise a montré que les sources du risque de « business » changent selon le type de « business model » des banques. Ainsi, la plupart des banques suivant un modèle de banque de détail ont montré une bonne capacité de résistance dans la crise, même si leurs coûts sont relativement rigides. L'exposition d'une banque au risque de « business » est donc fonction de son aptitude à maintenir son niveau de rentabilité.

Dans cette perspective, l'étude exploite les développements récents de la méthodologie des frontières d'efficience pour proposer une modélisation originale du risque de « business » reposant sur l'estimation d'une fonction de profit bancaire. Cette méthodologie permet de prendre en compte des ajustements coordonnés des coûts aux revenus aussi bien que l'absence de tels ajustements. Elle est appliquée aux données sur longue période (1993-2012) de plus de quatre-vingt dix établissements français mettant en œuvre une activité de banque de détail.

La distance de toute banque par rapport à la frontière de profit, où sont localisées les meilleures pratiques de son groupe stratégique, mesure son score d'efficience en termes de profit. Toute dégradation du score sous l'effet de changements non prévus des volumes d'activité traduit un déclin de sa profitabilité. Ainsi, la période étudiée vérifie que les plus fortes dégradations résultent de chocs de demande (récession de 1993, crise récente) : les plus mauvais scores illustrent les pires situations rencontrées par les banques confrontées à la réalisation des chocs sur leurs activités. Les chocs peuvent ainsi être définis par tirage dans la queue de distribution des scores, c'est-à-dire en traitant toute banque comme pouvant être précipitée dans le groupe des banques les moins profitables. Dès lors, la comparaison des scores obtenus en estimant une frontière de profit de long terme et une frontière de profit « choquée » mesure la baisse du profit induite par des chocs tout en neutralisant l'impact de

l'inefficience managériale sur la profitabilité. L'étude considère plus spécialement les chocs affectant soit la demande de services de liquidité, soit la demande de crédit, deux activités constitutives de la banque de détail.

Les résultats apportent une confirmation de la solidité des banques de détail en situation de crise. La chute de la profitabilité apparaît largement soutenable au regard de la sévérité des chocs considérés dans l'étude. Ainsi, en cas de choc sévère sur l'activité de crédit, le profit chute modérément si les coûts sont ajustés rapidement, plus nettement s'ils ne peuvent l'être. Un choc sur la création de services de liquidité a des effets un peu moins marqués. Au total, la capacité de résistance des banques tient logiquement à la continuité de l'activité de collecte des dépôts mais elle dépend aussi du maintien de l'offre de crédit plutôt que de pratiques restrictives des banques en ce domaine. Les autres activités de la banque de détail revêtent un caractère moins stratégique. En cas d'impossibilité d'ajuster les coûts opératoires, il faudrait en réalité un choc très marqué précipitant toutes les banques sans exception dans la frange des 5% les moins rentables pour réduire le profit de l'année à néant. Le risque de volatilité de l'activité apparaît donc maîtrisé dans la banque de détail, dont l'histoire bancaire a montré que la rupture exerce les effets les plus dévastateurs sur l'économie.

1. Introduction: business risk concept and measurement

Every firm is subject to business risk. Business risk refers to potential losses due to adverse, unexpected changes in business volume, margins and costs. These losses can be the result of changes in customer preferences, an increase in competitive pressures or other changes in a bank's environment. Thus, business risk also corresponds to managerial risks, and it depends on the firm's capacity to adapt its policy to unexpected events and changes. In banking, business risk is a non-financial risk that is linked to the uncertainty of earnings not associated with financial risks (market, credit, ALM risks) or other types of non-financial risk (operational risk). Banks' business risk must not overlap with these other risks, not does it incorporate interest rate risk, default risk or credit risk because these risks are already taken into account in other forms of risk.

The banking sector devoted little attention to business risk before the subprime crisis. As mentioned in a 2007 economic capital survey, "management of business risk still lags behind core financial risks" (IFRI/CRO, 2007). The survey demonstrated that business risk is considered an important risk type – over 85% of participants include it in their economic capital frameworks, and the average impact is 10% of the aggregate economic capital requirement. However, business risk is probably also the risk type that is being debated most actively at present, with discussions focusing on the most appropriate measurement approach. A variety of approaches are taken to reflect business risk, and the level of sophistication generally appears to be less pronounced than in the case of core financial risks. For this key 'non-financial' risk, "a range of different capital calculation approaches can be employed that could lead to significantly different results and, as a result, management incentives". Overall, there is no clear convergence in the approach to measuring business risk.

One reason for this lack of attention to business risk in the banking industry is that in the booming financial markets of the 1990s and 2000s, business risk hardly seemed to be a significant risk for banks. But the recent subprime crisis demonstrated that banks can suffer from this business risk more than non-financial firms. Indeed, during the crisis, the extinction of some bank activities can be considered to be the consequence of business risk. For example, activity in the markets for syndicated loans, structured products and IPOs dropped substantially, or even disappeared altogether, due largely to severe asset depreciations and strong financial market disruptions. Consequently, the revenues of most investment banks declined sharply. The relatively flexible cost structure of investment banks allowed them to adjust costs quickly, but business risk casts doubt on the resiliency of this bank business model.

By contrast, the recent crisis has revealed the existence of stronger resiliency factors in the retail banking business model. Even if retail banking is characterized by a relatively rigid cost structure, most deposit-taking banks focused on retail banking businesses have come through the recent crisis quite well. By transforming local deposits into lending in the areas where people live and work, retail banks benefit from a quite stable financing structure which allows them to maintain lending activities in period of stress. They can act as "shock absorbers" rather than transmitters of risk to the financial system and the real economy. This is because they are exposed to a low level of credit risk on average, even if credit risk concentrations - especially in the real estate sector - could be an issue, and also because they can better manage funding liquidity risk. Overall, the recent crisis has shown that the specification of business risk sources varies across banks' activities and business models.

Today, banking supervisors call for more attention to be paid to business risk. The Basel Banking Committee on Banking Supervision requires it to be taken into account in Pillar II, the internal regulatory framework of Basel II. Recent Basel III proposals aimed at strengthening the resiliency of the banking sector are heading in the same direction. Thus, the new regulatory framework is encouraging banks to look at this risk. Nevertheless, regulators concede that this risk is "hard to measure".

This paper proposes a new approach for modeling and measuring business risk based on the efficiency frontier methodology. More specifically, it exploits the duality property between the directional distance function and the profit function. Thus, any increase in one bank's distance to its efficiency frontier may be considered to be the consequence of a decline in that bank's profitability. Using this approach, we take the performance of the banks located in the last percentiles of inefficiency scores as illustrating the worst situation a bank will potentially encounter if unfavourable business risk factors materialise. The paper uses a unique database containing regulatory information about balance sheets and income statements for more than 90 French banks – mainly regional and cooperative banks - that can be identified as running a retail banking business model. Data are collected on a half-yearly frequency over the 1993-2011 period. This sample contains all banks belonging to major French banking groups.

It is organized as follows. Section 2 presents a survey of the current methods used to measure business risk. Section 3 outlines the proposed directional distance function methodology. Section 4 presents the data and the specification of the frontier. Section 5 discusses the results and section 6 concludes.

2. Survey of current methods used to measure business risk

While current estimation methodologies of business risk use purely statistical models, we propose a structural model which is based on recent developments in the production and cost theory applied to the banking sector.

2.1. Earnings-at-risk methodologies

The current methods used to model business risk can be classified in two categories: the benchmark approach and the earning-at-risk (EaR) approach.

The first one proposes to compute specific earnings risk for each business unit of a given bank by taking specialized banks as benchmarks. In other words, the earnings volatility of different bank business models is derived from the assessment of specialized banks' earnings volatility. Thus, it consists in finding a panel of specialized banks and taking information about their earnings volatility as a proxy for the volatility of the corresponding business line in an universal bank.

The second method, the EaR method, compares a bank's earnings volatility with the rigidity of operating costs. and measures business risk in terms of the volatility of bank net income. It consists in computing historical earnings volatility with banks' internal data (long-term time series on volumes, margins, revenues or costs) and in transforming this volatility into a measure of earning-at-risk (EaR). The simplest way to obtain such a measure of business risk is to assume a specific distribution for the profit components, to then compute the earnings at a given level of confidence, a sort of "worst case" earnings, and finally to determine the loss under these assumptions. As a first step, the probability distribution of revenues from fees and commissions and revenues from interest are built, and a given quantile is chosen. Then, as a second step, operating costs are assumed to be totally constant in the short run (with a one-year horizon, in fact), and they are subtracted from expected revenues to determine expected earnings. However, an extension of the approach could decompose costs into fixed and variable costs.

Using a statistical approach, Klaus Böcker (2008) proposed a stochastic model to determine the EaR and quantify business risk. He suggested a multivariate continuous-time model for the future cash flows of the different earnings' components chosen. Under this model specification, he computed the value of the EaR on the basis of the distribution property of the chosen equation of earnings' components. Then, he determined a dynamic relation between the EaR measure and the capital-at-risk measure (the economic capital needed for business risk).

One weakness in this EaR approach is that it is quite demanding in terms of the length of the time period. Another weakness is that it requires business risk to be isolated from other forms of risk. Indeed, revenue volatility could be strongly driven by other types of risks. But it is not so easy to isolate different risk sources.

2.2. A structural approach to business risk

Here, we propose an alternative measure of business risk based on a structural approach to modelling bank technology and measuring bank performance. As noted by Hughes and Mester (2010) this approach is choice-theoretic, and it relies on a theoretical model of the banking firm and the concepts of cost minimization or profit maximization. In this approach, the bank is viewed as a firm whose main objectives are to solve information problems in lenders-borrowers' relationships, to manage risks and to provide liquidity services to the economy. As demonstrated in the banking literature, commercial bank's uniqueness or superiority over other financial firms is largely derived from its high leveraged capital structure, e.g. the funding of informationally opaque borrowers with short term deposits. Such foundations help to understand the business model of retail banks and to choose accordingly the inputs and outputs in the bank production.

When discussing the economic performance of a producer, it is common to describe it as being more or less "efficient". The firm's efficiency refers to the differences between observed and optimal values of its inputs and outputs. In practice, efficiency is measured by comparing observed and optimal cost, revenue or profit. How one measures bank performance in the structural approach depends on whether one views the bank as an entity that minimizes inputs or maximizes profit. The structural approach relies on the economics of cost minimization or profit maximization. Estimating a profit function seems more relevant when the issue is to compute business risk because it might tell us if the bank is "economically efficient", that is not only whether managers organize the production so that the amount of output produced is maximized, which corresponds to "technical efficiency", but also whether they correctly choose the level of inputs and outputs and their combination so as to respond to changes in relative prices, changes in demand for products and other changes in a bank's environment, which corresponds to "economic efficiency". Moreover, to the extent that bank decisions affect bank risk, this approach fits well with the objective of measuring the overall risk of banking production in the face of specific and systematic economic shocks.

Business risk affects the bank performance. In retail deposit-taking banks, business risk comes primarily from sources which are linked to the two main functions of these banks: lending, and the provision of liquidity. Indeed, due to the regular decline of deposits in the portfolios of private agents, retail banks are increasingly exposed to the risk of a shortage of short-term funding. They are also confronted with growing competition in lending markets. Retail banks also suffer from potential volatility in non-interest income, that is, from changes in commissions and other fee income owing to changes in the volumes of various financial or insurance products and payment services. The structural approach of bank performance measurement allows considering all these potential sources of business risk into the specification of the production function. Consequently, in this paper, we consider lending and liquidity provision as the main outputs of the banking production process which can be impacted by shocks.

More precisely, business risk refers to situations in which decreases in profits result from adverse changes owing to uncertainty over output volumes, margins and costs. Because output uncertainty creates volatility in banks' profits, shocks to the outputs produce unexpected changes to output volumes. Business risk is defined as the gap between optimal profit before adverse shocks to the outputs and observed profit after shocks. It is measured by the gap between the initial benchmark efficiency frontier and the shocked frontier. This gap corresponds to an increase in profit inefficiency, which is actually a decline in profits. Adverse shocks affect profits and move banks away from their efficiency frontier and correspond to an increase of the distance to the pre-shocks frontier. In other words, for a given bank, and a given output's volume shock, the increase in this distance represents the decrease in profits owing to the decline in the outputs' volume. But to compute inefficiency coming from adverse shocks, we have to neutralize inefficiency coming from differences in management ability. To do that, we translate all individual banks towards the pre-shock and post-shock frontier, "as if" all banks were equally efficient in terms of management capacity.

Therefore, our measurement proposition consists in using the methodology of the efficiency frontiers and more precisely the parametric directional distance function to build a profit inefficiency measure that allows similar banks to be ranked in terms of their ability to maximize profit. This choice is based on the duality between the directional distance function and the profit function, as demonstrated by Färe and Grosskopf (1997) and Färe et al (2004). The volatility of earnings can be computed by the distance volatility, which varies depending on the uncertainty of volumes, margins or costs of the bank. A change in volumes, margins or costs affects the distance and thus the inefficiency measure. The variability of the distance corresponds to the EaR, which is a measure of the variability of profit efficiency. Moreover, it is possible to choice a functional form of the distance function that allows linking directly the distance – that is the profit – to any change in the combination of inputs and outputs which depicts the intermediation function of the bank. Consequently, we can consider as well shocks on outputs such lending supply as well as shocks on the bank funding.

When considering the business risk, this methodology offers the advantage of taking into account the possibility of a simultaneous contraction of inputs and expansion of outputs in constructing the profit efficiency frontier. Thus, the technical inefficiency measure derived from a directional distance function is more complete than the more restricted measures derived from an input distance function or output distance function. Then, if we simulate a succession of shocks, the set of consecutive distance increases in the sample represents the distribution of individual profit losses. An extreme value in this distribution serves as a measure of the EaR. Indeed, taking an extreme value means that we retain one of the most severe consequences of the shock in terms of a decrease in profits. We use non-parametric Monte-Carlo simulations to compute a large number of shocks and consecutive business risk values.

Finally, our approach provides a kind of stress-test of the bank resiliency. Stress testing describes various techniques used by individual banks to assess their potential vulnerability to exceptional but plausible adverse events or shocks. Stress tests have become an integral tool of bank's risk management (Drehman, 2008), and they are also techniques that are frequently used by banking supervisors to gauge the resiliency of the financial system as a whole. The most common of these techniques involves the determination of the impact on the portfolio of a bank of a given scenario that creates a simultaneous change in a combination of specific risk factors.

3. Methodology: the directional distance function

As mentioned above, Färe and Grosskopf (1997) emphasized the duality between the profit function and the directional distance function. Using the directional distance function, Färe et al (2004) measured profit efficiency in US banks, and Park and Weber (2005) recently presented similar measures for Korean banks. The first paper decomposes profit technical inefficiency into allocative inefficiency and technical inefficiency, while the second focuses on inefficiency changes and productivity changes. More recently still, Chaffai and Dietsch (2009) used this approach to measure the influence of environmental characteristics on branches' profitability. In this study, we use the methodology of the parametric directional distance function to build an inefficiency measure and to take the volatility of this inefficiency indicator as a measure of business risk. Indeed, profit volatility allows us to give consideration to the impact of volume changes on banks' profits.

The directional distance function methodology has three advantages. First, it allows a simultaneous contraction of the inputs and expansion of the outputs in constructing the efficiency frontier, which is based on the duality between the directional distance function and the profit function. Thus, technical inefficiency measurement is more comprehensive than the restricted measures derived from an input distance function or the output distance function. These two functions are dual to the cost function and revenue function respectively. Second, the aggregate inefficiency of a banking group is the sum of the individual inefficiencies of each bank (Färe et al, 2005). Third, less information is required for the estimation of the directional distance function than for the profit function. In fact, only information on output and input amounts is needed, thus avoiding problems arising from the difficulty of measuring prices (which are needed to estimate the profit function), which are particularly severe in banking applications when using accounting data[2].

3.1. The parametric directional distance function

We consider that each bank uses a vector of inputs $X = (x_1, x_2, \ldots, x_k) \in \Re_k^+$ to produce a vector of outputs $Y = (y_1, y_2, \ldots, y_p) \in \Re_p^+$. Let T denote the production possibilities set of all the combinations of inputs *X* which can produce the vector *Y*. We also assume that

[2] That could particularly be the case for banks' cost of real physical which is very hard to measure using accounting data.

this set satisfies the familiar regularity conditions[3]. The directional distance function encompasses the data in the direction vector $g = \left(-g_x, g_y\right)$ and is defined by:

$$\vec{D}\left(X, Y; -g_x, g_y\right) = \underbrace{Max}_{\beta}\left\{\left(X - \beta g_x, Y + \beta g_y\right) \in T\right\} \tag{1}$$

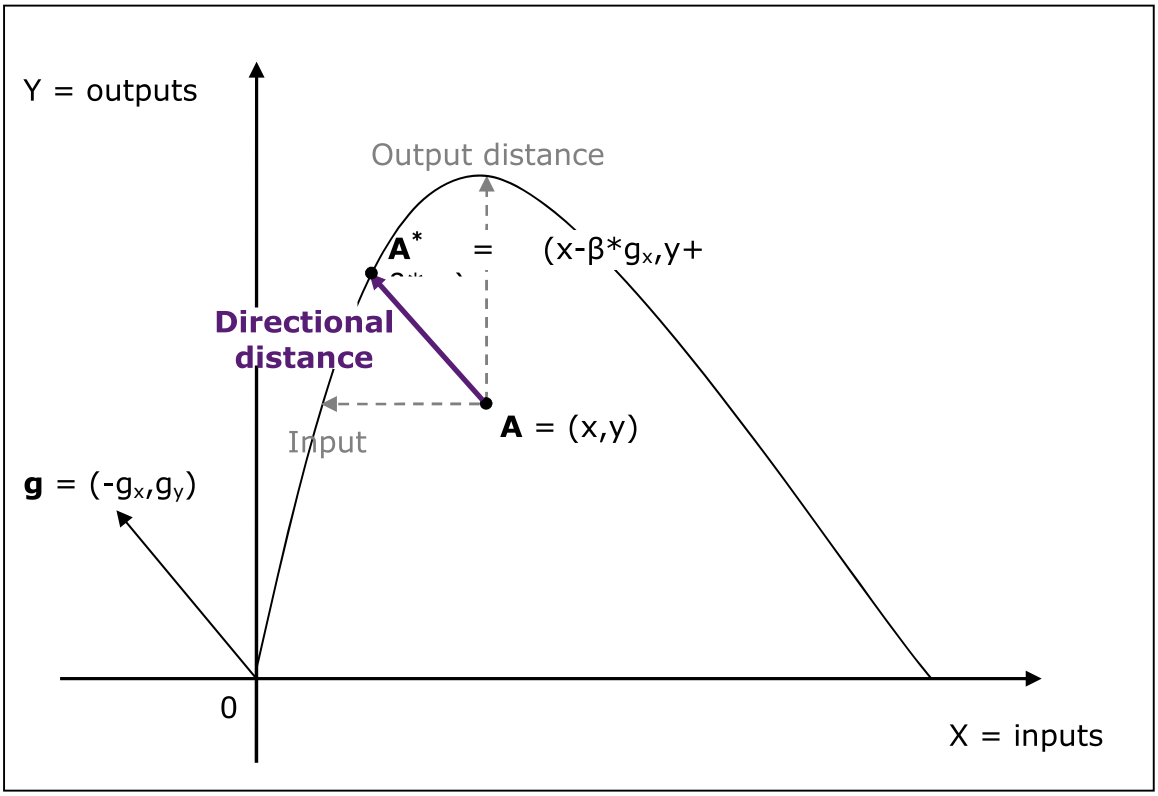
The directional distance function is defined by simultaneously expanding the outputs and contracting the inputs in the direction *g*, which needs to be specified. The scalar β solution of (1) will measure the maximum expansion of outputs and contraction of inputs technically possible. For any combination of inputs and outputs, profit is at its maximum when the bank is on the frontier, which corresponds to $\beta = 0$. If not, $\beta > 0$ and the bank could boost profits by improving its technical efficiency in the g-directional vector.

It is important to mention that the measure of inefficiency derived from this model depends on the direction vector g in which the data are projected on the frontier. Two important particular direction vectors should be mentioned. The first direction $g = \left(0, g_y\right)$ only allows for an expansion of outputs given a level of inputs. This model refers to the output distance function which is dual to the revenue function. The second direction $g = \left(-g_x, 0\right)$ allows for input contraction given the level of produced outputs, which refers to the input distance function. Here, we retain the direction $g = \left(-g_x, g_y\right) = \left(-1, 1\right)$ which allows us to measure the technical efficiency that the bank can achieve if it increases its revenues and reduces its costs in the same proportion.

To illustrate this distance function, we consider figure 1. Bank A is projected in A* by estimating the frontier for all banks. The distance AA* for bank A measures gross technical inefficiency incorporating both technical inefficiency and allocative inefficiency.

[3] The set T is non-empty and convex. Both outputs and inputs are freely disposable.

Figure 1: Illustration of the direction distance function



To estimate the frontier, two methods could be used: the non-parametric method, which uses the linear programming methodology, and the parametric-econometric method, which is known as the stochastic frontier approach. In this paper, we choose the stochastic frontier to estimate the directional distance function. The main reason for this choice is that this method distinguishes random noise and technical inefficiency under a bank's control.

The directional distance function should verify the translation property[4] (Chambers et al (1996)). Not all flexible functional forms such as the Translog function or the Fourier function verify this property. Chambers (1998) proposed the flexible quadratic functional form. This form is linear with respect to the parameters, and it provides a good representation of banking production. It has been used in several studies devoted to banks (Färe et al (2005), Park and Weber (2005)), among others, and it appears to be the only one used in the actual empirical studies dealing with the directional distance function. The estimation of the model needs to add linear restrictions to the model parameters in order to verify the translation property.

[4] The directional distance function satisfies the translation property if
$\vec{D}(X-\alpha g_x, Y+\alpha g_y; -g_x, g_y) = \vec{D}(X, Y; -g_x, g_y) - \alpha$

In our specification, we add time parameters to take temporal changes into account. Thus, the quadratic directional distance function is:

$$\vec{D}\left(X,Y;-g_x,g_y\right)=\alpha_0+\delta_0 t+\frac{1}{2}\delta_1 t+\sum_{j=1}^{p}\phi_j Y_j t+\sum_{i=1}^{k}\psi_i X_i t+\frac{1}{2}\sum_{j=1}^{p}\sum_{j'=1}^{p}\alpha_{jj'}Y_j Y_{j'}+\sum_{j=1}^{p}\alpha_j Y_j+\sum_{i=1}^{k}\gamma_i X_i+$$
$$\frac{1}{2}\sum_{i=1}^{k}\sum_{i'=1}^{k}\gamma_{ii'}X_i X_{i'}+\sum_{j=1}^{p}\sum_{i=1}^{k}\eta_{ji}Y_j X_i$$
(2)

with the following linear restrictions to verify the translation property:

$$\begin{cases} \sum_{j=1}^{p}\alpha_p g_y-\sum_{i=1}^{k}\gamma_i g_x=-1 \\ \sum_{j=1}^{p}\phi_j g_y-\sum_{i=1}^{k}\psi_i g_x=0 \\ \sum_{j=1}^{p}\eta_{ji} g_y-\sum_{i'=1}^{k}\gamma_{ii'} g_x=0 \quad i=1,...,k \\ \sum_{j'=1}^{p}\alpha_{jj'} g_y-\sum_{i=1}^{k}\eta_{ji} g_x=0 \quad \mathrm{j}=1,...,p \end{cases}$$

In addition, the symmetry restrictions are imposed: $\alpha_{jj'}=\alpha_{j'j}$ and $\gamma_{ii'}=\gamma_{i'i}$.

To estimate the parameters of the directional distance function, we used the stochastic frontier approach. The stochastic specification of the directional function was proposed by Färe et al (2005) and takes the form:

$$0=\vec{D}\left(X,Y;-g_x,g_y\right)+\varepsilon \tag{3}$$

where $\varepsilon=v-u$, $v\sim \mathrm{N}\left(0,\sigma_{\mathrm{v}}^2\right)$ and $u\sim \mathrm{N}^+\left(0,\sigma_{\mathrm{u}}^2\right)$.

Then, we apply the translation property of the directional distance function to the previous equation with respect to one of the outputs of the model, Y_p for example. Using the directional vector $g=\left(-g_x,g_y\right)=\left(-1,1\right)$, we obtain:

$$-Y_p=\vec{D}\left(X-g_x Y_p,Y+g_y Y_p;-g_x,g_y\right)+\varepsilon \tag{4}$$

and the stochastic frontier becomes:

$$-Y_p = \alpha_0 + \delta_0 t + \frac{1}{2}\delta_1 t + \sum_{j=1}^{p-1}\phi_j\left(Y_j + Y_p\right)t + \sum_{i=1}^{k}\psi_i\left(X_i - Y_p\right)\mathrm{t} + \sum_{j=1}^{p-1}\alpha_j\left(Y_j + Y_p\right) + \sum_{i=1}^{k}\gamma_i\left(X_i - Y_p\right) +$$

$$\frac{1}{2}\sum_{j=1}^{p-1}\sum_{j'=1}^{p-1}\alpha_{jj'}\left(Y_j + Y_p\right)\left(Y_{j'} + Y_p\right) + \frac{1}{2}\sum_{i=1}^{k}\sum_{i'=1}^{k}\gamma_{ii'}\left(X_i - Y_p\right)\left(X_{i'} - Y_p\right) + \sum_{j=1}^{p-1}\sum_{i=1}^{k}\eta_{ji}\left(Y_j + Y_p\right)\left(X_i - Y_p\right) + v - u$$

(5)

In equation (5), $u \geq 0$ is a one-sided disturbance term which captures technical inefficiency, and *v* is a usual normal two-sided noise disturbance. This frontier could be estimated using the maximum likelihood method or the method of moments (Kumbhakar and Lovell, 2000).

In the previous equation, *u* is assumed to follow a half-normal distribution and *v* a normal distribution. We assume, too, that two error components are independent. The set of parameters $\left\{\delta_0;\delta_1;\alpha_0;\alpha_1,\ldots,\alpha_p;\gamma_1,\ldots,\gamma_{k-1};\alpha_{11},\ldots,\alpha_{p-1p-1};\gamma_{11},\ldots,\gamma_{kk};\eta_{11},\ldots,\eta_{p-1k};\sigma_u;\sigma_v\right\}$ is estimated using the maximum likelihood method. This information can be used to compute the estimated value of $-Y_p$ and then the value of the global residual $\hat{\varepsilon} = \hat{v} - \hat{u} = -Y_p - (-\hat{Y}_p)$.

Here, we assume that *u* is half-normal. The inefficiency components are obtained by taking the expected value of *u* conditional on *(v-u)*, as is suggested by Jondrow et al (1982).

The main advantages of the stochastic approach are (i) that the model takes into account possible noise in the data and (ii) that it is possible to conduct inference tests of the value of model parameters. But, it presents the disadvantage of not imposing the inequality restrictions on the derivatives of the directional distance function[5].

3.2. Using the parametric directional distance function to measure retail banks' business risk

The distance, as defined in the previous section, provides a profit-inefficiency score at the bank level. A profit-efficient bank has a score equal to 0 (this bank is located on the

[5] The other disadvantage is the endogeneity problems with the inputs. The solution could be to use instrumental variable estimators instead of the maximum likelihood method. But the decomposition of the u terms from the residuals still remains.

frontier of "best practices"), whereas a bank with a score equal to β% ($\beta > 0$) could increase profit by β %.

In this study, we use the directional distance function to measure business risk, meaning situations in which decreases in profits result from adverse changes owing to uncertainty over output volumes, margins and costs. Because we assume that output uncertainty creates volatility in banks' profits, we have to implement shocks to the outputs in this framework, representing unexpected changes to output volumes. The idea is that these shocks imply a decrease in profits which corresponds to an increase of the distance value. In other words, for a given bank, and a given output's volume shock, the increase in distance represents the decrease in profits owing to the decline in the outputs' volume. Thus, if we consider a succession of shocks, the set of consecutive distance increases in the sample represents the distribution of individual profit losses. An extreme value (high 90% and 95% percentiles) in this distribution serves as a measure of the EaR. Indeed, taking an extreme value means that we retain one of the most severe consequences of the shock in terms of a decrease in profits. We use non-parametric Monte-Carlo simulations to compute a large number of shocks and consecutive business risk values.

The simulation procedure to compute business risk is as follows:

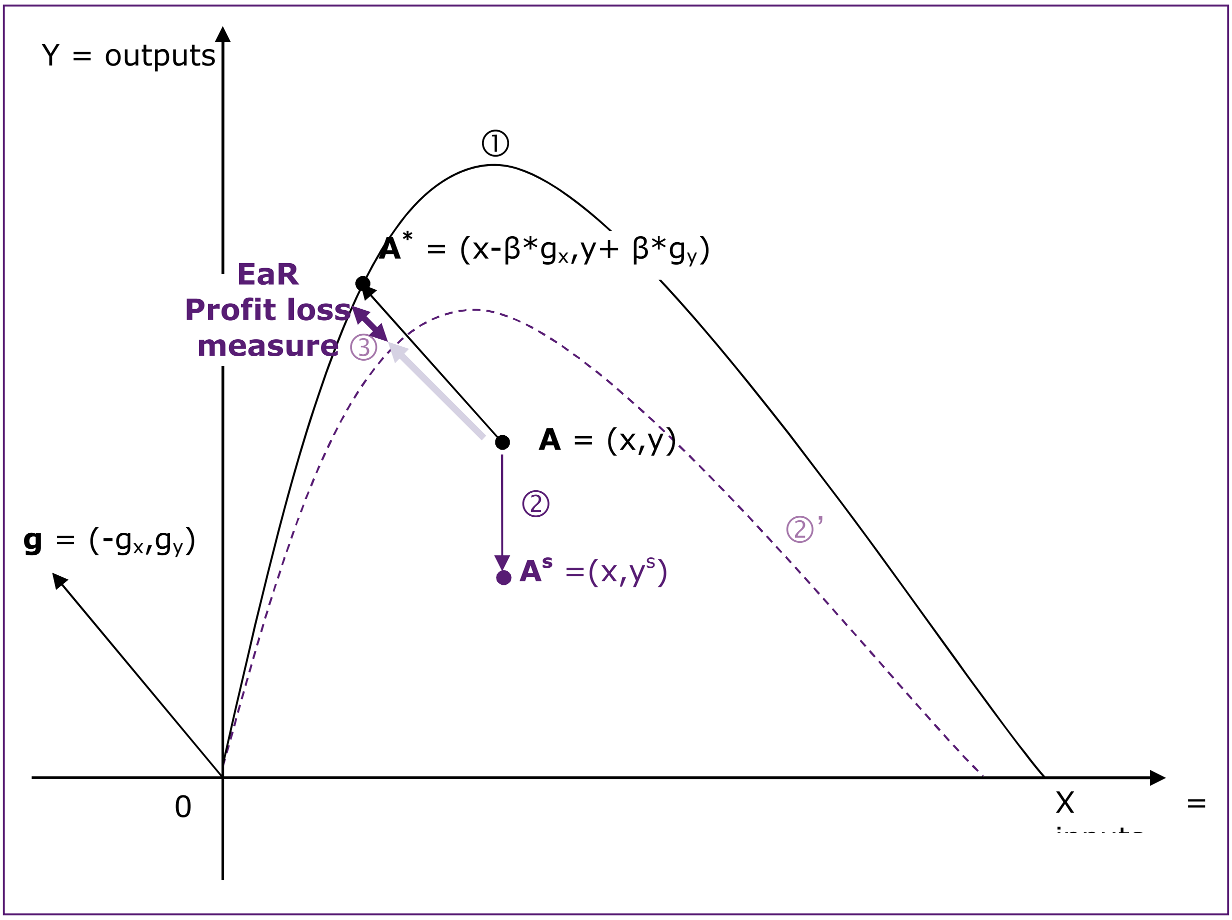
- In a first step, we estimated the parametric directional distance, taking into account the observed technology and the observed inputs-outputs combinations. The distance to the frontier of "best practices" provides a measure of profit inefficiency that will serve as a benchmark for the next-steps comparisons (① in figure 2).
- In a second step, we generated shocks to outputs by using a drawing procedure we will present below. Thus, each output's volume is modified (in fact, reduced) by a certain percentage at each drawing (② in figure 2). Then, we re-estimated the distance function, taking into account new shocked values of bank outputs and new values of inputs-outputs combinations (②' in figure 2) so as to obtain a new shocked frontier. We note that if shocks reduce volumes, profit-inefficiency increases and the new "shocked frontier" is below the initial one; it means that the distance increases, too.
- In a third step, we computed the difference between the distance given by the shocked frontier when we take initial observed outputs and inputs, and the distance to the initial benchmark frontier (③ in figure 2). The difference measures the business risk, which is actually the reduction in profits measured by an increase of profit inefficiency generated by the shocks to the outputs' volumes:

$$Risk = \left(\hat{\vec{D}}\left(X_{it}, Y_{it}; \hat{\beta}\right) - \hat{\vec{D}}\left(X_{it}, Y_{it}; \hat{\beta}^{s}\right)\right) / \hat{\vec{D}}\left(X_{it}, Y_{it}; \hat{\beta}\right) \qquad (6)$$

where the initial frontier is $\hat{\vec{D}}\left(X_{it}, Y_{it}; \hat{\beta}\right)$ and the shocked frontier is $\hat{\vec{D}}\left(X_{it}, Y_{it}; \hat{\beta}^{s}\right)$

This procedure, which consists in computing the difference between the frontiers, also offers the advantage of neutralizing changes in inefficiency owing to managerial inefficiency. Figure 2 illustrates the simulation procedure, which is done separately for each output.

Figure 2: Illustration of the simulation procedure



The difference in distances provides a measure of business risk for each shock to a given output. Each shock affects all banks of the sample. Thus, for each simulation, because our sample is composed of 91 banks over an 19-year time period and a half-yearly frequency (see below), we get 3,276 values for the gap between frontiers. Then, we retain the 90% and 95% percentiles of the distribution of these differences as earnings-at-risk values for each simulation. The simulation procedure is replicated N times, so that we obtain N values for business risk corresponding to N distinct shocks. The final value for business risk (earnings-at-risk) resulting from shocks to this output is given by the average value of the N high percentiles values we have obtained for each iteration.

The value of the chosen percentile depends upon the objective of the study and the size of the sample. We choose two sufficiently large percentiles to cover potential losses due to severe shocks, but not too high to avoid extreme values. It is the reason why we retained the 90% and 95% percentiles, which appears to be a good compromise. By implementing such quite large shocks, the idea in this paper is to provide a kind of stress-test. Our methodology allows taking account for any realistic change of the outputs. To determine the proportion of the change in the volume of each output associated to specific scenarios calls for other methodologies which are complementary to ours.

To implement output shocks, we have chosen a realistic and simple procedure, which consists in drawing in the inefficiency scores distribution itself. Indeed, this distribution exhibits the observed sample's profit volatility, which is assumed to be the consequence of real shocks determined by the business cycle. Such shocks have affected the banks over the 19-year time period under study. For instance, an inefficiency score of 10% in a given year for a given bank is assumed to be the consequence of adverse economic conditions affecting that bank in that year. More precisely, for each drawing, we get a value of the bank's inefficiency (for instance, a 5% inefficiency value), and we assume that the volume of each output is reduced by the same proportion. Such a drawing procedure implies that the shocked output decreases at each drawing. The proportion represents the output change that impacts on bank profitability. Then, we re-estimated the distance frontier using these new values for each output. We used the same logic for each output individually, and for the three outputs, and we computed the difference between the initial estimated frontier and the new estimated frontier as a measure of each bank's business risk. Note that this difference reflects only the impact of shocks, and not the impact of managerial or operational inefficiency. The value of this difference gives a measure of each bank's profit reduction which is the consequence of each shock.

The scenario we have implemented consists in drawing in the same 10% percentile of the distribution of inefficiency scores, whatever the year[6].

6 We also implemented a second scenario which consists in drawing in the last 10% percentile of the distribution of inefficiency scores, taking only the worst years into account, which corresponds in fact to strong shocks. The results of this second scenario are very close. Consequently, we will concentrate the presentation on the first one.

4. Data and specification of the profit function

The sample is composed of quite all French banks running a retail banking business model. It includes 91 French banks we have identified as running a retail banking business model. Retail banking is identified by considering the share of loans to the households and small businesses clients in the asset side of the balance sheet, and the share of deposits of the same clients in the liability side. This sample is mainly composed of regional cooperative banks forming the four main networks of French mutual banks – Banques Populaires, Caisses d'Epargne, Caisses de Crédit Agricole and Caisses de Crédit Mutuel – but the sample also contains corporate banks, such as CIC banks or Crédit du Nord[7]. We excluded large French banks such as BNPP or Société Générale because the accounting information we use does not allow to be truly isolate the performance in retail banking and in investment banking. The study uses half-yearly balance sheets and income data[8] over the period from 1993-2011. Thus, our sample is constituted of more than 3,200 half-yearly observations of banking firms. Over the nineteen-year period covered by this study, a large number of mainly internal M&A operations have modified the geography of regional cooperative banking groups. We have registered all these operations to build our final bank sample, merging the accounting data of banks involved in M&A operations.

In this study, we focus on business risk in retail banks. So, it is necessary to integrate all the sources of risk of a retail bank into the specification of the distance function. Indeed, the measure of inefficiency may be sensitive to the specifications of the inputs and outputs vectors.

Here, we do not use the conventional intermediation and production approaches to specify model inputs and outputs and consequently, we do not use stocks of assets or liabilities as measures of banking outputs. Instead, we use a value-creation approach, which uses flows of services and may be justified as follows. Modern banking theory highlights two main "raisons d'être" for banks: to provide funding to dependent borrowers who do not have any other sources of external funding, and to provide liquidity to the economy. To assume these economic roles, banks produce: i) information services through borrower screening and monitoring activities, and ii) liquidity services

[7] An institutional peculiarity of large French mutual banks groups is that the regional banks are the groups' main shareholders. Thus, detailed regulatory reports are available at both the regional bank level as well as at the consolidated group level.

[8] The data come from regulatory accounting reports, which facilitate reliable and homogenous data.

by implementing a fractional reserve methodology (to provide funding liquidity) or trading activities (to provide market liquidity).

To produce such services, banks use various technologies: i) brokerage technologies, which are "pure" intermediary technologies in which banks do not transform the characteristics of assets, and ii) "transformation" technologies, in which banks perform a qualitative asset transformation, which implies a *mismatched* bank balance sheet in terms of risk, liquidity and maturity. Using these techniques, retail banks provide various flows of services: information services through lending, liquidity provision services to depositors and short-term creditors, and financial and brokerage services[9]. Bank customers are prepared to pay for these services. This approach to banking production allows banking services to be identified and distinguished from financial services. The approach also invites a measurement of banking outputs in terms of income flows[10].

Therefore, the model considers these three main outputs of retail banks, linked to the main functions of banks and largely measured in terms of income flows. The outputs are lending services, liquidity services and financial and brokerage services. The latter one consists in implementing a financial transformation process using financial market instruments and in selling savings products and insurance products, and corresponds to the supply of portfolio and other financial consultancy services. These three types of services provide the main sources of revenues in retail banking. These revenues are provided in two forms: i) directly, in the form of fees and commissions which are direct prices for the sale of credit card services and other services linked to the management of customer accounts, as well as for the sale of insurance or savings products, and ii) indirectly, as a component of interest margins on loans and deposits. Thus, it is necessary to adopt a methodology to identify the component of interest margins which corresponds to the purchase of banking services. Consider, first, the measurement of the component of interest margins serving as compensation for the lending services supplied by banks. In this case, the interest margin should be computed by taking the "spread" between the interest rate paid by the borrower and a "reference" interest rate. Formally, this "reference" interest rate is the compensation the investor receives for forgoing current consumption in exchange for future consumption. This compensation includes a

[9] To provide such low-default services, banks have to bear risks and manage transformation processes. They are implementing inter-temporal risk smoothing (which cannot be diversified) by holding assets and liabilities of different characteristics in their balance sheet, and cross-sectional risk-sharing that contributes to financial markets equilibrium, which necessitates the use of efficient risk management techniques.

[10] See also Wang and Basu (2006) and Wang, Basu and Fernald (2008). For these authors, balance sheet or "stocks" measures of bank outputs do not coherently reflect the role of banks as processors of information and transaction services, because they are based on a hypothesis of "fixed proportionality" between the flow of services and stocks of financial products, which is not always verified in practice.

premium for the relevant risks (such as liquidity risk or default risk, including the risk of the bank's insolvency) associated with the provision of funds by creditors. This compensation is free of any elements of banking services. Thus, the effective interest rate paid by the borrower contains a compensation for the investor who supplies the funds and bears the risks, and a compensation for the lending services supplied by the bank, which corresponds to the "spread". Only this spread should be taken as the compensation for lending services. Finally, the sum of commissions on loans and this "spread" measures lending services as a banking output. The same logic is applied to measure liquidity services provided to banks' customers: it is the sum of commissions on liquidity services provided and a "spread" which is a component of the interest rate margin on deposits. This spread is measured by the difference between: i) the rate of return the bank gains when it invests the deposits collected in money and interbank markets, and ii) the interest rate the bank pays to depositors. This spread compensates the bank for the provision of liquidity services. The third output is measured following the same approach, adding the interest margin on securities and treasury transactions to commissions directly associated with portfolio and insurance brokerage services provided by the bank.

In this approach of banking production, all banking services are flows of output which are measured by the explicit and implicit prices that banks' customers are willing to pay for such services. These services are produced by implementing a transformation process using real resources and "risk" capital. Two inputs are real inputs by nature: labor and physical capital. The real inputs are measured by the corresponding costs. Labor costs are measured by the salaries paid to employees and the expenses connected with the use of real physical capital (office rental costs and information systems costs) by the corresponding operating charges. The third input reflects the fact that to perform risk-bearing activities and provide low-default risk products and services, retail banks have to maintain equity capital, the role of which is to absorb potential unexpected losses. Equity capital provides such protection against a bank's insolvency risk.

Table 1 provides descriptive statistics of the sample banks' outputs and inputs.

Table 1: Descriptive statistics in the banks' sample (in €1,000)

	Y1	Y2	Y3	X1	X2	X3
Mean	190 244	186 532	306 512	128 739	114 502	711 938
Median	134 611	113 446	5 251	94 552	71 240	438 330
Std	273 330	302 976	2 955 635	175 091	278 161	1 370 549
Min	-472 512	-68 210	-4 484 694	102 33	10 858	-69 887
Max	3 504 366	5 299 506	5.30e+07	1 976 325	4 199 188	1.57e+07

Source: ACPR and authors' calculations

5. The results

5.1. Profit inefficiency measurement – the "benchmark frontier"

First, we estimated the directional distance function corresponding to the frontier with three inputs and three outputs. The method used for estimating the parameters is the stochastic maximum likelihood method. The inefficiency component is assumed to follow a half-normal distribution. It represents profit inefficiency and gives a value equal to the inefficiency score. Remember that we chose the directional vector $g = (-g_x, g_y) = (-1, 1)$, which allows us to measure the degree of technical efficiency that the bank can achieve if it increases its outputs and reduces its inputs in the same proportion.

We present the distribution of inefficiency scores in table 2 and figure 3. Remember that the distance is a measure of the degree of bank inefficiency. Therefore, a bank with a low score is more efficient than a bank with a high score (banks located on the frontier have a score equal to 0).

Figure 3: Distribution of inefficiency scores

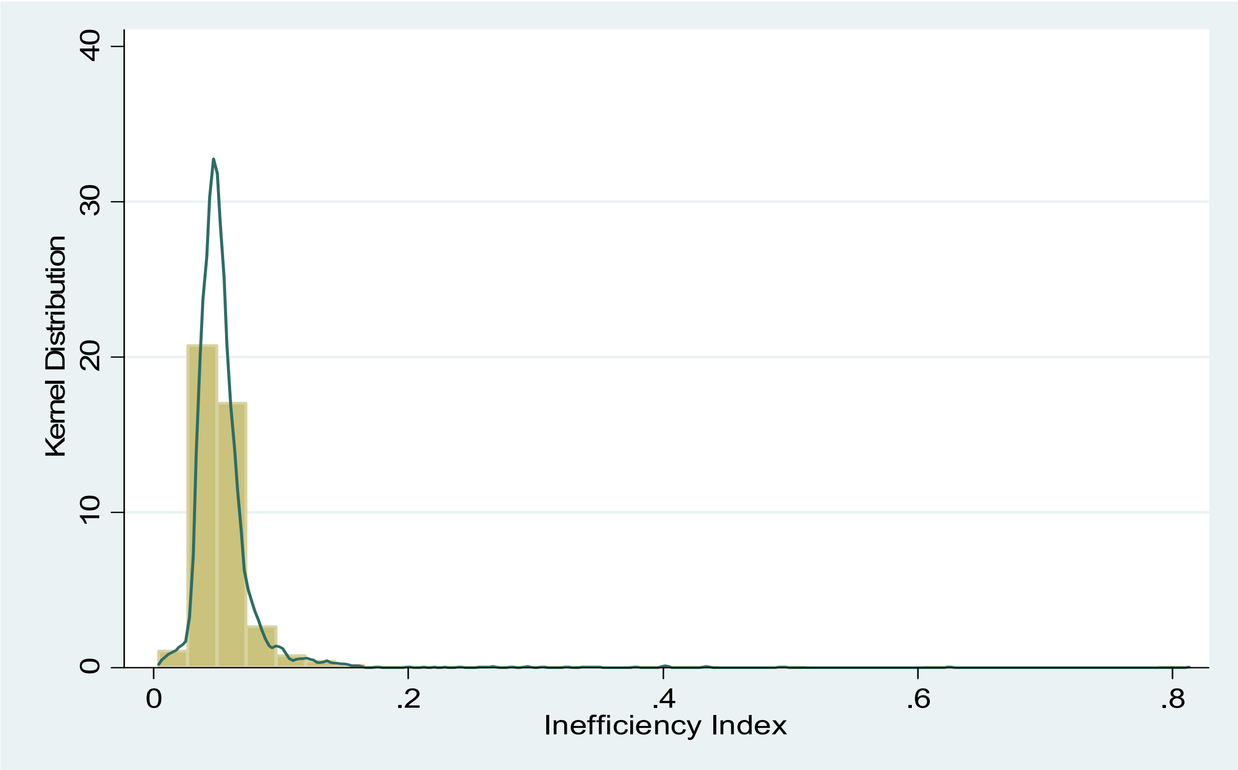
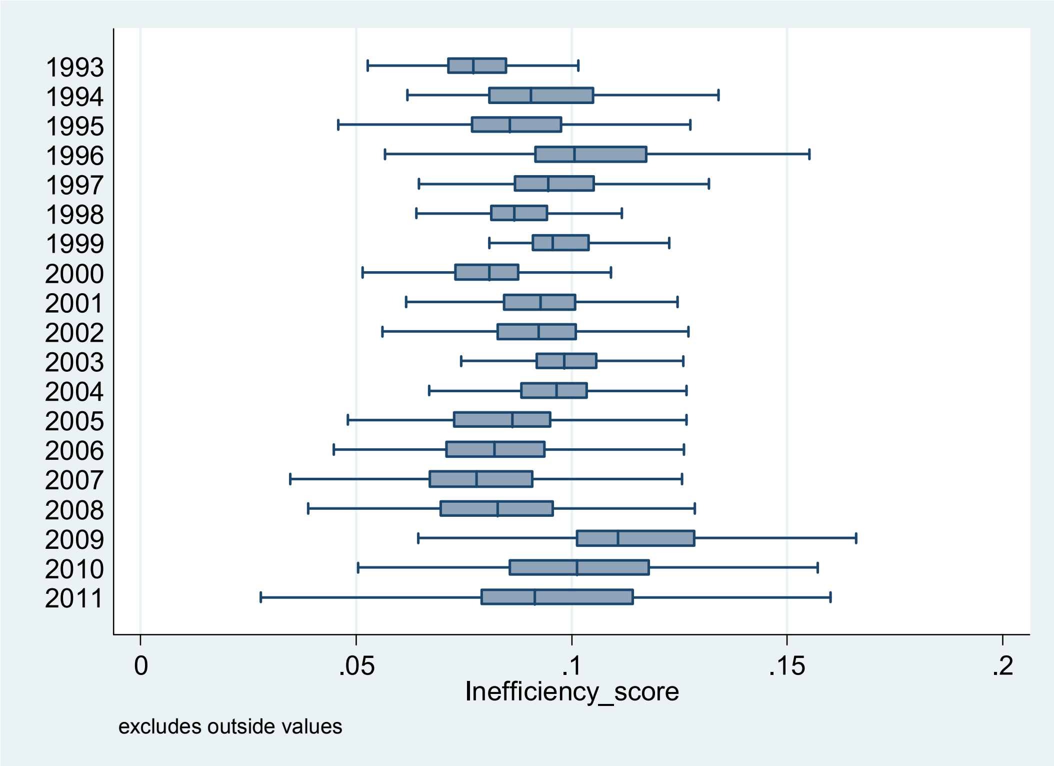


Table 2: Distribution of the inefficiency scores in the sample (in %)

	P5	P10	Q1	Median	Mean	Q3	P90	P95
Inefficiency score	3.2	3.6	4.2	5.0	5.5	6.0	7.4	8.9

Figure 4 illustrates the volatility of the distance to the initial frontier over the 1993-2011 time period (end-of-year data). On the one hand, the inefficiency score dispersion is quite large each year. On the other hand, the inter-temporal variability across the business cycle can be highlighted. Indeed, the average annual score clearly appears to be affected by the business cycle. We have verified that the lowest values of efficiency scores are correlated with the worst economic conditions. Accordingly, the worst values of the scores correspond to periods of severe recession in France (1994-1996, 2003, and 2009-2011).

Figure 4: Dispersion of inefficiency scores by year



5.2. Business risk measurement – simulation results

We now present the results of the simulations. Business risk is defined as the response by a bank's profits to adverse shocks to the outputs. It is measured by the gap between the initial benchmark frontier and the successive shocked frontiers. This gap corresponds to an increase in profit inefficiency, which is actually a decline in profits. In the following, the business risk measures are presented as a percentage of total profit.

As mentioned above, we defined a scenario which consists in drawing in the 10% last-percentile distribution of inefficiency scores, all years – good or bad - included. For each output, we replicated this procedure 500 times so that we obtained 500 values for each bank's business risk (measured either by the 90% or the 95% percentiles of the distribution of gaps between frontiers), corresponding to 500 distinct shocks to a given output. The final value of the business risk (earnings-at-risk) due to shocks to this output is given by the average value of the 500 high-percentiles values obtained at each stage of the simulation.

We consider two polar cases depending on the possibility for banks facing a shock to reduce their costs:

- In the first case, we assume that input amounts – that is, costs – can be reduced in the short term. Consequently, we use the "profit" specification of the distance function to estimate profits, and we choose the directional vector $g=(-1,1)$, which allows us to measure inefficiency if the bank could reduce its costs in the same proportion as the outputs. In this case, the bank can adjust its cost structure in the face of a shock to its main income sources.
- In the second case, we assume that inputs are rigid and cannot be reduced in the short term. Consequently, we have used the "revenue" specification of the distance function, choosing the directional vector $g=(0,1)$. In this case, the bank is unable to reduce its costs when confronted with sudden unexpected shocks to its main revenue sources.

We note that for each simulation, the shock magnitude is the same for each output. The assumption that the volume of each output is reduced in the same proportion is mainly illustrative[11]. This assumption allows us to compare the results between outputs in terms of business risk.

Table 3 below presents measures of business risk in percent of total profit of the banks' sample, and for the two cases (with cost adjustment and without). As mentioned above, drawing in the last quartile of the original inefficiency score distribution simulates strong shocks to outputs, as shown by the previous distribution of inefficiency scores (table 1). Indeed, on average, the shock represents an average output reduction of around 30% in that case. On the other hand, drawing in the complete distribution of scores is equivalent to assuming an average reduction of 12% of outputs, which actually corresponds to a significant shock to business volumes or to demand for banking services.

[11] Here, adverse shocks are built by drawing in the efficiency scores distribution which is a synthetic measure of performance. So, technically, using a methodology based on distance function invites to consider similar shocks to different outputs. Using different proportions for different outputs would need to estimate, outside the model, the sensitivity of outputs to the macro variables which define adverse scenarios.

Table 3: Measures of business risk as the value of the 90% and 95% percentiles of the distribution of profit decreases following major shocks to banks' outputs: (business risk defined as declines in profit in % of total profit)

	With costs adjustment g (-1,1)			*Without costs adjustment g (0,1)*		
Percentiles	Shocks to lending services	Shocks to liquidity services	Shocks to other services	Shocks to lending services	Shocks to liquidity services	Shocks to other services
90%	4.4	3.5	2.9	16.9	14.1	8.9
95%	6.5	4.1	3.4	110.9	90.7	53.3

In this simulation, major shocks to outputs are computed by multiplying every bank's output by the value of inefficiency scores obtained by drawings in the last quartile of the distribution of inefficiency scores.
For instance, if we consider a "strong" shock to a bank's loans, the estimated value of business risk is equal to a 4.42% decrease in that bank's total profit if i) we take the 90% percentile of the simulated distribution of the bank's profits after the shock and ii) we consider that the bank can adjust its costs. It reaches a 6.53% profit decrease if we take the 95% percentile. If the bank cannot adjust costs, the reductions reach 8.88% and 53.9%, respectively, of total profit. Note that shocks to demand for deposits and to other services produce weaker declines in profits if the banks can adjust costs and stronger declines in profits if they cannot.

First, our results verify the resiliency of the retail banking business model. Indeed, business risk – measured by profits at risk – is quite low in the case of strong shocks to outputs. To find very large instantaneous decreases in profits, we have to assume that banks have no capacity to reduce real inputs in the short term in the face of a strong shock to demand for other services (which is actually demand for insurance or savings products) and in the worst possible scenarios – which corresponds to the 95% percentile of the profit inefficiency distribution.

Second, whether costs can be adjusted or not following an output shock, results show that shocks to lending services provoke the strongest declines in profits (equal to 4.4% and 6.5% of total profits, and 16.9% and 110.9% of total profits, depending on the bank's capacity to reduce costs or not, when we consider the 90% and 95% percentile). This result might be the consequence of the higher sensitivity of a bank's profits to the supply of this kind of services. Indeed, lending activity is likely to be the most strategic, if not the most profitable, activity for retail banks. During all periods of financial crisis, that is, in the periods 1993-1995, 2001-2003, or more recently, 2008-2009, lending activity decreases quite substantially. Moreover, the lending market during the 2000s was characterized by strong interbank competition, which eroded the interest rate income that banks earned on loans. If we consider liquidity provision services, the sensitivity of this source of profit is not so much lower than that of lending activity. In fact, this sensitivity is, to a large extent, attributable to the volatility of interest rates which determines the margin on deposits. Lastly, concerning the provision of insurance services, where revenues are derived principally from fees paid by households as banks' customers, even in periods of financial crisis, revenues from this type of activity seem less volatile, due to large inertia effects.

To summarize, results show that the decline in bank's profitability is quite sustainable even if banks are impacted by quite severe demand shocks. The ability to adjust real costs certainly plays a crucial role in this result. Recall that in our approach we create shocks by drawing in the tail of the distribution of efficiency scores. That is we assume that most banks reach the situation of the worst banks of the sample. And, even if retail banks all together would reach this situation, the value of the decrease in profits given by our results (a decrease of profit equal to around 10% per year if we cumulate the three outputs shocks at the 90% percentile), would likely not deplete their available capital buffers before several years.

6. Conclusion

As the recent financial crisis has demonstrated, business risk should be considered as one of the major risks facing the banking industry. However, this type of risk did not affect all banks with the same intensity during the crisis. Some banks appeared to be more resilient to shocks than others, depending on the main business model they were running. This is notably the case for retail banks, which seemed to be less affected by the crisis than financial institutions running other business models. Indeed, the recent crisis has revealed the existence of stronger resiliency factors in the retail banking business model. Even if retail banking is characterized by a relatively rigid cost structure, most deposit-taking banks focused on retail banking businesses have come through the recent crisis quite well. In fact, the crisis has shown that the specification of business risk sources varies across banks' activities and business models.

This paper proposes a new approach to modeling and measuring business risk, and it uses this approach to compute business risk in banks running a retail banking business model. This new methodology is based on the efficiency frontier framework and, more specifically, on the directional distance function. It relies on the duality property between the distance function and the profit function to provide a measure of business risk as lost profits. Indeed, the directional distance function facilitates an estimation of profit decreases induced by adverse shocks to banking outputs. Such shocks replicate the worst financial situations banks have encountered in the 1993-2011 time period covered by the study. In addition, the methodology allows simultaneous changes in outputs and inputs to be taken into account. This approach is well founded on the theoretical foundations provided by the microeconomics of production, cost and profit. Moreover, the approach is data-efficient because only data on input and output amounts are required. The approach can also serve as a new methodology to implement stress testing in banking. The innovation here is to treat every bank as if it could fall in the last 10 percentiles of the less profitable ones, and to compute the distance between non-shocked frontiers and shocked frontiers, while neutralizing profit decreases emanating from non-macroeconomic or systemic shocks, such as those arising due to inefficient management.

In this study, the methodology is applied to a quasi exhaustive sample of French banks – mainly composed of cooperative regional banks – which have all been identified as running a retail bank business model. We measure business risk in two situations: a situation where retail banks facing shocks to output volumes have the capacity to reduce their costs, and a situation where bank costs are rigid in the short term. We also model shocks in a consistent manner and consider shocks of different intensities.

Our findings confirm the strong resiliency of the retail bank business model. Indeed, business risk – profit declines caused by adverse output shocks - is low in the case of moderate - but significant - shocks to outputs, and this risk appears to be sustainable in the case of strong shocks to output volumes, even if banks are unable to adjust costs to output changes in the short term. Moreover, results show that retail banks' profits are more affected by shocks to lending services and to liquidity provision services than by shocks to households' portfolio services. In particular, shocks to lending services provoke the highest decrease in profits, which means that retail banks' profits are the most sensitive to the supply of this kind of services. In other words, lending activity is likely to be the most strategic, if not the most profitable, activity for retail banks, protecting banks against business risk.

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Appendix 1.

Table A1: Maximum likelihood parameter estimates of the directional distance function
Stochastic frontier parameter estimates, normal/half normal distribution

variable	Direction(gy=1,gx=-1)	
	Est.	t-statistic
tr	-0.0027	-2.52
trs	0.0004	3.8
sy2py1t	0.0045	9.09
sy3py1t	0.0331	29.88
sx1my1t	-0.0057	-7.7
sx2my1t	0.0046	6.98
sx3my1t	-0.0007	-1.46
sy2py1	0.0240	4.31
sy3py1	0.2333	14.65
sx1my1	-0.0095	-0.98
sx2my1	-0.0851	-8.76
sx3my1	0.0099	1.42
sy22	-0.0055	-4.11
sy33	-0.0404	-15.97
sy23	0.0345	12.36
sx11	0.0014	0.46
sx22	0.0011	2.28
sx33	-0.0096	-9.71
sx12	-0.0032	-2.23
sx13	0.0063	4.68
sx23	-0.0086	-7.46
sy2x1	0.0037	2.51
sy2x2	0.0005	1.01
sy2x3	0.0031	2.3
sy3x1	0.0077	4.65
sy3x2	-0.0049	-3.32
sy3x3	-0.0345	-22.59
intercept	-0.7809	-126.88
σu	-5.8428	-108.76
σv	-5.2247	-59.94
Aic	-8138.8326	
Log likelihood (#obs)	4099.4163 (3264)	

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