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Performance and Merton-Type Default Risk of Listed Banks in EU: a panel VAR approach

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Abstract

This paper provides empirical evidence that sheds new light into the dynamic interactions between risk and efficiency, a highly debated issue in the literature. Using a large panel data set that includes 251 listed banks operating in the enlarged European Union over the period 1998 to 2006 this study exploits a three-step procedure. First, we estimate three alternative measures of bank performance, based on alternative efficiency definitions, by employing a directional distance function framework, along with a cost frontier and a profit function. As a second step, we calculate a Merton type bank default risk, based on the Black and Scholes (1973) option pricing theory. Then, we employ a Panel-VAR analysis, which allows the examination of the underlying relationships between efficiency and risk without applying any a-priori restrictions. Most evidence shows that the effect of a one standard deviation shock of the distance to default on inefficiency is negative and substantial. There is some evidence of a reverse causation, but the impact of a shock in bank inefficiency on risk is small and lasts for a short period of time. As part of a sensitivity analysis, we extent our study to investigate the relationship between efficiency and default risk for banks with different types of ownership structures and across financial systems with different levels of development.

JEL classification: G21; G28; D21.

Key words: bank inefficiency, default risk, panel VAR, causality.

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1. Introduction

One of the greatest challenges that financial institutions in general and banks in particular face is coping with increasing uncertainties and accompanying risks. This has become particularly crucial in the context of the current financial turmoil, which has highlighted a miss-assessment of risk on behalf of banks, investors, as well as supervisors, with overwhelming and far reaching implications for financial stability. The importance of risk is certainly not limited to the banking sector, yet it bears greater weight for this sector, given the hefty financial and economic consequences of a bank failure (Caprio and Klingebiel, 1997). These consequences are not limited to financial losses for the shareholders, clients and deposit guarantee schemes and to loss of competition, but can potentially also cause destabilization of the financial system through contagion mechanisms, leading to a banking crisis. Bank failures further disrupt the flow of credit to local communities, reduce money supply and have adverse effects on the real economy (Caprio and Klingebiel, 1997).

The challenge of safeguarding financial stability has become even more vital in recent years in light of the new global financial environment that has rapidly evolved, characterized by enhanced financial liberalization and integration, rapid development of new financial products and technologies, as well as consolidation in the banking industry and increasing competition (Moshirian, 2008). All of the above pose additional pressure on banks to effectively manage their risk, while ensuring a high level of efficiency.

There are several studies that have tried to investigate the appealing relationship between efficiency and risk. Most researchers (Berger and DeYoung, 1997; Williams, 2004; Podpiera and Weill, 2008) have focused on the relationship between efficiency and credit risk, usually proxied by problem loans or loan loss provisions. A related strand of the literature has examined the relationship between risk and efficiency by incorporating in the efficient frontier various aspects of risk (see among others Hughes and Mester; 1993; Mester, 1996; Hughes et al., 2000 Altunbas et al., 2001; Maudos et al., 2002; Pastor and Serrano, 2005). Other researchers have applied a two-stage approach to examine the link between efficiency and risk, where inefficiency is regressed on a set of variables capturing risk. This type of analysis does not provide evidence of causality between the two concepts, but rather examines whether certain risk characteristics are more prevalent among inefficient banks (see for example Maudos et al., 2002; Hauner, 2004; Carvallo and Kasman, 2005; Yildirim and Philippatos, 2007). Finally, another strand of the literature has investigated the relationship between efficiency and bank failure (Berger and Humphrey, 1992; Wheelock and Wilson, 1995) and found that failing banks tend to locate far from the efficiency frontier. Moreover, Barr and Siems (1994) used efficiency as an explanatory variable in failure-prediction models for detecting a bank's troubled status, while Podpiera and Podpiera (2005) also find evidence that cost inefficiency should be included into early warning systems.

However, despite the apparent interest in investigating the relationship between efficiency and risk, no study has, so far, provided comprehensive evidence on the causality between them. In addition, at the theoretical level results are also limited and inconclusive. In particular, Goodhart et al. (2004) argue that financial stability is endogenously determined together with economic efficiency within a general equilibrium model, whilst they point to the existence of a trade-off between them. This could indicate a possible negative relationship between efficiency and risk. On the other hand, other studies (see Allen and Gale, 2004 and Boyd and De Nicolo, 2005) argue that such a trade-off may not exist. Further empirical evidence is, therefore, warranted.

The aim of this paper is to fill this gap in the literature and to provide for the first time a comprehensive assessment of the causal relationship between bank efficiency and risk in the European banking industry by employing a novel econometric approach, the panel Vector Autoregression (VAR) analysis. As the theory has not offered any silver bullets regarding what causal relationships one should expect, this approach allows us to estimate the underlying dynamic relationships between inefficiency and risk without applying any a-priori restrictions.

In detail, we employ a three-step procedure. First, we estimate three measures of bank performance based on alternative efficiency definitions. As Berger and Mester (1997) point out, measured efficiency differs across various efficiency concepts, as each one adds some independent informational value in the analysis. Thus, making use of alternative efficiency measures should be a compelling way to strengthen our results and their policy implications. In particular, this paper estimates productive, cost, and profit efficiency. The first concept corresponds to technical inefficiency and is a purely physical notion, which is defined in terms of the distance to a production frontier without recourse to price information. For the estimation of productive efficiency we depart from the traditional Shephard functions and employ an advanced technique developed by Chambers et al. (1996), that is, the directional technology distance function. Directional distance functions are natural performance measures while they also entail a flexible description of technology allowing banks to optimize by seeking simultaneously the maximum expansion of outputs and contraction of inputs that is technologically feasible (Färe et al., 2007). On the other hand, the concepts of cost and profit efficiency are based on the assumption that financial firms pursue an economic behavioural goal, whether cost minimization or profit maximization and as Berger and Mester (1997) argue, they have solid economic foundations.

In a second step, we calculate bank default risk, using stock market data. Among the plethora of risk measures proposed in the literature, our choice of the distance to default is justified, as it is an all-encompassing market-based measure of banks' default risk (Gropp et al., 2004). This measure has the advantage over traditional risk proxies, based on accounting data, of using the forward-looking information incorporated into security prices. More specifically, it combines information about stock returns with leverage and volatility information, thus capturing the most important determinants of default risk.[1]

Finally, we employ a panel VAR analysis to examine the underlying dynamic relationships between efficiency and risk in a comprehensive way. By using VAR on panel data we are able to disentangle the complex relationship between inefficiency and risk, while allowing for bank specific unobserved heterogeneity. We focus on two main questions. First, how do the VAR's endogenous variables, inefficiency and risk, respond dynamically to their own and other variables' shocks? Second, which shocks

[1] Empirical studies on default risk have mainly examined the ability of bank default probabilities to predict bank failures. For example, Gropp et al. (2004) analysed the ability of the distance-to-default to signal bank fragility and found leading properties of 6 to 18 months, while Chan-Lau et al. (2004) measured bank vulnerability for 38 banks in 14 emerging market countries using the distance-to-default and showed that it can predict a bank's credit deterioration up to nine months in advance. In a more recent study, Lepetit et al. (2008) investigate the relationship between default risk and product diversification in the European banking industry.

are the primary causes of variability in the inefficiency and risk? The reduced form panel VAR analysis provides answers to these questions as it is free from imposing a-priori assumptions concerning endogeneity, while all variables are treated as endogenous. Also, the panel-VAR methodology allows the estimation of orthogonalised Impulse-Response Functions (IRFs) and variance decompositions (VDCs).

As part of a sensitivity analysis, we extend our work to investigate the relationship between efficiency and default risk across banks with different ownership structures and across financial systems with different levels of development. Several studies have found that foreign banks on average perform poorly compared to private domestic institutions in developed nations (e.g., DeYoung and Nolle 1996, Berger et al., 2000), though results seem to be reversed in the case of developing countries (i.e., Bonin et al., 2005; Claessens et al., 2001; Fries and Taci, 2005). Foreign ownership is also found to be associated with more competitive national banking systems (e.g., Claessens and Laeven 2004, Martinez Peria and Mody 2004); and more credit for business (e.g., Berger et al., 2005) in developing countries. Thus, we examine the interaction between efficiency and risk for banks with different types of ownership by testing whether this relationship differs between foreign and domestic banks.

In addition, in light of the variety of financial systems across Europe, and especially in view of the differences between *'old'* and *'new'* EU Member States, we assess the role of financial development on the relationship between efficiency and risk. Despite the increasing degree of financial integration achieved over the last couple of years, European financial markets vary widely with respect to size, depth, efficiency and competition. Demirguc-Kunt and Huizinga (2000) argue that the level of financial development has a significant impact on bank performance. In particular, they show that underdeveloped banking markets tend to be characterised by inefficiencies and wide interest margins, and that financial deepening increases competition, enhances efficiency and lowers profits. To this end, we construct an index of financial development proposed by Demirguc-Kunt and Levine (1996) to examine the interaction between efficiency and risk for two groups; high and low financial development countries.

Following the above three step procedure and the sensitivity analysis, this paper contributes to the literature in several ways. First, to our knowledge, this is the first study to examine the underlying dynamic relationship between bank efficiency and risk within a Panel VAR context, allowing us to infer empirical evidence on a highly debated issue. Second, we employ three alternative efficiency measures, as a way of strengthening the validity of our results, while, in order to measure bank risk, we calculate the distance to default, which is considered to be a more comprehensive measure of risk than the commonly used index-number proxies based on accounting data. Third, we use a large and up-to-date dataset which covers the vast majority of listed banks in the enlarged EU, and that was compiled by combining three different databases. Fourth, we perform a sensitivity analysis by examining whether the relationship between risk and efficiency is influenced by the structure of bank ownership and by the level of financial development.

A quick glimpse at the results shows a negative relationship between inefficiency and the distance to default, while the causality runs from risk to inefficiency. The reverse causal relationship, from inefficiency to risk, can not be excluded for some of our alternative specifications, though the empirical evidence is weaker. The sensitivity analysis confirms overall that causality runs from risk to efficiency, though some variability is also observed across various subsamples.

The rest of the paper is structured as follows: Section 2 presents the main hypotheses we test in our study, while Section 3 provides the empirical specification of the models employed. Section 4 deals with data issues and describes the variables used and Section 5 provides the empirical estimations and discusses results. Finally, section 6 offers some concluding remarks and possible policy implications.

2. Hypotheses to be tested

Next, we specify the various hypotheses that could describe the underlying interaction between risk and inefficiency.

Hypothesis 1: *An increase in bank default risk causes an increase in bank inefficiency.*

This hypothesis, which closely relates to the *'bad luck'* hypothesis of Berger and DeYoung (1997), states that an increase in bank risk, which is translated into an increase in bank's probability of default, will cause managers to operate less efficiently. This is because bank managers that face soaring risk will have to take additional precautions and to incur additional risk-monitoring costs so as to preserve the quality of bank portfolio. In other words, bank managers will divert their attention away from solving day-to-day operational problems and from pursuing efficiency improving strategies to preventing a further deterioration of their financial position. In addition, in the extreme case that a bank is in a perilous financial situation, close to or bellow the threshold of default, it will face dear costs in order to defend its safety and soundness record to supervisors and market participants. In both cases, one would expect that higher costs, caused by an increase in bank default risk, would trigger an increase in bank inefficiency. Thus, under this hypothesis, we expect higher bank default risk to increase inefficiency.

Another possible explanation for the positive relationship from risk to inefficiency is the '*efficient market'* hypothesis (Fama, 1965). Since our measure of risk is primarily influenced by developments in the stock exchange, and in particular securities prices that incorporate forward-looking information, events such as the recent credit and liquidity crises, should find their way on bank stock prices that, in turn, would feed into a higher probability of default. Lowering the distance to default would then affect inefficiency measures, which are derived from balance-sheet data that reflect developments with an annual lag. Thus, in the context of an efficient stock market the causality would run from risk to inefficiency.

Hypothesis 2: *An increase in bank inefficiency causes an increase in bank default risk.*

An extension of the *'bad management'* hypothesis (Berger and DeYoung, 1997) could provide a possible explanation for the positive relationship between inefficiency and risk, but with the reverse causality. In this case, low scores of inefficiency could be seen as signals of poor senior management practices, which apply not only to day-to-day operations but also to risk monitoring and management. Poor managers who do not sufficiently monitor their operating expenses, nor do they effectively increase their profitability, as reflected in low measured cost and profit efficiency, could also practice inadequate risk management techniques. For instance, *'bad'* managers may take on negative net present value projects, or invest in lower quality loans. Thus, the reduction in measured efficiency, caused by *'bad management'*, may lead to poor risk management practices and unavoidably to mounting risks. As risks pick up, unexpected losses start to materialise, while soaring delinquencies further deteriorate a bank's financial position. Thus, under this hypothesis, high inefficiency would cause higher default risk.

Hypothesis 3: *A reduction in bank inefficiency causes an increase in bank default risk.*

Under the '*moral hazard'* hypothesis (Gorton and Rosen, 1995), entrenched managers of an efficient bank may have the incentive and a larger degree of manoeuvre from shareholders, to follow an expansionary strategy, which ex-post could be proved to be excessively risky. Given that most bank products and services include a promise for a future payment, it may take time for a bank's failure to fulfil its contracts to become evident (Bar and Siems, 1994). This could also be related to the *'skimping'* hypothesis of Berger and DeYoung (1997). Under this hypothesis banks seem more efficient because they may opt to cut operating costs, by rolling over bad loans or by increasing the size of their balance sheets, at the expense of facing higher risk.

Hypothesis 4: *An increase in bank inefficiency causes a reduction in bank default risk.*

Departing from the *'skimping'* hypothesis of Berger and DeYoung (1997), other things being equal, an increase in bank inefficiency in the short run could cause a reduction in risk taking activities that eventually may result to a reduction in bank default risk with a lag. This could imply that bank managers apply *'risk-averse'* management that in the short run would raise operating costs and thus also raise inefficiency, but it would reduce default risk. Along these lines Hughes (1999) argues that banks may apply risk-averse management induced by uncertainties related to a potential costly episode of financial distress or due to asymmetric information. We call, therefore, this hypothesis the *'risk-averse management'* hypothesis.

3. Empirical Methodology

3.1 Productive efficiency under a directional technology distance function framework

To model the production function and measure productive efficiency, we depart from the traditional Shephard distance functions and use the directional technology distance function proposed by Chambers et al. (1996). We assume that technology (T) for each bank is defined as the set of all feasible input-output vectors:

$$T^k = \{(x^k, y^k): x \in R_+^N, y \in R_+^M, x \text{ can produce } y\}. \quad (1)$$

where k is the number of banks and $x^k \in R_+^N$ are inputs used to produce $y^k \in R_+^M$ outputs. The directional technology distance function completely characterizes technology and allows firms to optimize by seeking simultaneously the maximum expansion of outputs (y) and contraction of inputs (x) that is technologically feasible. Given a directional vector, denoted by $g = (g_x, g_y)$, $g_x \in R_+^N$ and $g_y \in R_+^M$, that determines the direction in which technical efficiency is assessed, the directional distance function can be defined as:[2]

$$\vec{D}_T(x, y; g_x, g_y) = \sup\{\beta : (x - \beta g_x, y + \beta g_y) \in T\} \tag{2}$$

We choose to set $g = (g_x, g_y) = (1, 1)$ which implies that the amount by which a bank could increase outputs and decrease inputs will be $\vec{D}_T(x, y; 1, 1)$ units of x and y. For a bank that is technically efficient, the value of the directional distance function would be zero, while values of $\vec{D}_T(x, y, g_x, g_y) > 0$ indicate inefficient production.

To empirically estimate the directional distance function we can either use a mathematical approach (i.e. the data envelopment analysis) or a parametric approach. In this paper, we follow Färe et al., (2005) and opt for a stochastic frontier method (SFA), originally proposed by Aigner et al., (1977) and Meeusen and Van den Broeck (1977). This method allows the decomposition of the error term into two parts: the one-sided inefficiency term, reflecting managerial competence and the classical random error that captures any miss-measurement or misspecification errors.

We parameterize the directional distance function via a flexible quadratic functional form, which permits the imposition of the translation property. This specification corresponds to a multi-output/multi-input technology with technical progress captured by a trend variable. Non-neutral technical change is modeled by including terms

[2] The properties of the directional distance function are described in Chambers et al. (1998) and Färe and Grosskopf (2004). Among other things, the translation property says that if we translate the input-output vector (x,y) into $(x - \lambda g_x, y + \lambda g_y)$, then the value of the distance function is reduced by the scalar.

capturing the interaction between trend and inputs and trend and outputs.[3] The directional distance function is thus parameterized as:

$$\vec{D}_T(x, y; g_x, g_y, t, \theta) = \alpha_0 + \sum_{n=1}^{N} \alpha_n x_n + \sum_{m=1}^{M} \beta_m y_m + \frac{1}{2} \sum_{n=1}^{N} \sum_{n'=1}^{N} \alpha_{n'n} x_n x_{n'}$$
$$+ \frac{1}{2} \sum_{m=1}^{M} \sum_{m'=1}^{M} \beta_{mm'} y_m y_{m'} + \sum_{n=1}^{N} \sum_{m=1}^{M} \gamma_{mn} y_m x_n$$
$$+ \delta_1 t + \frac{1}{2} \delta_2 t^2 + \sum_{n=1}^{N} \psi_n t x_n + \sum_{m=1}^{M} \mu_m t y_m + \varepsilon \qquad (3)$$

where $\theta = (\alpha,\beta,\gamma,\delta,\mu,\psi)$ is a vector of parameters to be estimated and ε is a random error assumed to be independently and identically distributed with mean zero and variance σ_ε^2. Subtracting $\vec{D}_T(x, y; g_x, g_y, t, \theta) = u$ from both sides of (3) yields a functional form with a composite error term ε-u. The one-sided error term u represents bank-specific inefficiency and is assumed to be generated by truncation (at zero) of a normal distribution with mean μ and variance σ_u^2.

The parameters of the quadratic function must satisfy a set of restrictions, including the usual restrictions for symmetry ($a_{nn'} = a_{n'n}$, $\beta_{nn'} = \beta_{n'n}$) and the following restrictions that impose the translation property:

$$\sum_{n=1}^{N} \alpha_n g_n + \sum_{m=1}^{M} \beta_m g_m = 1, \; \sum_{n=1}^{N} \alpha_{nn'} g_{x_n} = 0, \qquad n'=1,\ldots,N,$$

$$\sum_{m=1}^{M} \beta_{mm'} g_{y_m} = 0, \quad m' = 1,\ldots, M, \quad \sum_{n=1}^{N} \psi_n = 0 \text{ and } \sum_{m=1}^{M} \mu_m = 0 \qquad (4)$$

[3] Note that in order to capture any heterogeneity across countries, we include country dummies in all empirical specifications.

The theoretical restrictions given in (4) are used to form a model that is suitable for estimation (see Färe et al., 2005).[4] We estimate the stochastic frontier model in (3) via a maximum likelihood procedure parameterized in terms of the variance parameters $\sigma_s^2 = \sigma_u^2 + \sigma_\varepsilon^2$ and $\lambda = \sigma_u / \sigma_\varepsilon$.

3.2 Cost and profit efficiency under a Stochastic Frontier Approach

To estimate cost and alternative profit inefficiency, we opt again for the stochastic frontier approach (SFA), which incorporates both noise and inefficiency into the model specification. In particular, in the case of the cost frontier, we assume the following specification:

$$TC_{it} = f(P_{it}, Y_{it}, N_{it}, Z_{it}) + v_{it} + u_{it} \tag{5}$$

where TC_{it} denotes observed total cost for bank i at year t, P is a vector of input prices Y is a vector of outputs of the firm, N is a vector of fixed netputs and Z is a vector of control variables. v_i corresponds to random fluctuations and is assumed to follow a symmetric normal distribution around the frontier and u_i, accounts for the firm's inefficiency that may raise costs above the best-practice level and is assumed to follow a half-normal distribution. To empirically implement the cost frontier, we opt for the following translog specification:[5]

[4] In particular, we use the translation property to obtain a specification of the parameterized quadratic function given by Equation (3), in which one of the inputs, *labour*, is selected as the dependent variable.

[5] The translog function has been widely applied in the literature due to its flexibility. Some papers (Mitchell and Onruval, 1996; Berger et al., 1997; DeYoung and Hasan, 1998) have found that the Fourier-flexible form, that combines a standard translog functional form with Fourier trigonometric terms, provide a better fit. However, Berger and Mester (1997) found that both specifications yielded essentially the same average level and dispersion of measured efficiency, and both ranked the individual banks in almost the same order. For simplification, we omit the subscripts for time ($_t$).

$$\ln TC_i = \alpha_0 + \sum_i a_i \ln P_i + \sum_i \beta_{\mathrm{i}} \ln Y_i + ½ \sum_i \sum_j a_{ij} \ln P_i \ln Pj + ½ \sum_i \sum_j \beta_{ij} \ln \mathrm{Y}_i \ln \mathrm{Y}_j$$

$$+ \sum_i \sum_j \delta_{ij} \ln P_i \ln \mathrm{Y}_j + \sum_i \varphi_{\mathrm{i}} \ln \mathrm{N}_{\mathrm{i}} + ½ \sum_{\mathrm{i}} \sum_j \phi_{\mathrm{ij}} \ln N_i \ln N_j + \sum_i \sum_j \xi_{\mathrm{ij}} \ln P_i \ln N_j$$

$$+ \sum_i \sum_j \zeta_{\mathrm{ij}} \ln Y_i \ln N_j + \theta_1 t + ½ \theta_2 \mathrm{t}^2 \sum_i \mu_{\mathrm{i}} t \ln P_i + \sum_i \kappa_{\mathrm{i}} t \ln Y_i + + \sum_i \nu_{\mathrm{i}} t \ln N_i$$

$$+ kD_i + \sum_i \xi_{\mathrm{i}} Z_i + u_i + v_i \qquad (6)$$

Standard linear homogeneity and symmetry restrictions in all quadratic terms are imposed in accordance with economic theory, while we also include country dummies to capture any differences across countries and time effects to account for technological progress.

The stochastic frontier model (6) is estimated via a maximum likelihood procedure parameterized in terms of the variance parameters $\sigma_\varepsilon^2 = \sigma_u^2$

$+ \sigma_v^2$ and $\lambda = \sigma_u / \sigma_\varepsilon$.

For the estimation of alternative profit efficiency, we follow a similar formulation. Based on Berger and Mester (1997) we prefer the alternative profit function over the standard profit function.[6] The alternative profit function uses the same explanatory variables as the cost function, which is a strong advantage in empirical work because usually information on the output price vector is not available with enough level of

[6] Berger and Mester (1997) argue in favor of using the concept of alternative profit efficiency over the cost or standard profit efficiency, especially in cases when there are unmeasured differences in the quality of outputs, or there is a scale bias (variable outputs are not completely variable), or markets are not perfectly competitive and the firms exercise some market power in setting output prices or due to inaccuracies in the output price data. Moreover, Berger and Mester (1999) argue that the alternative profit function fits the data better than the standard profit function.

disaggregation and accuracy (Mendes and Rebelo, 2003). The dependent variable now becomes *ln(π+θ+1)*, where θ indicates the absolute value of the minimum value of profits *(π)* over all banks in the sample. This transformation allows us to take the natural log of profits, given that profits can also take negative values. Also in the case of the profit function, the composite error term becomes $\varepsilon_i = v_i - u_i$ where u_i is assumed to follow an exponential distribution.

3.3 Panel VAR Analysis

Vector Autoregressive (VAR) methodology fits the purpose of this paper, given the absence of an a-priori theory regarding the relationship between the variables of our model. This methodology is based on a framework that allows all variables to enter as endogenous within a system of equations, where the short run dynamic relationships can be subsequently identified (Lütkepohl, 2006). Essentially, the VAR would allow us to explore the underlying causal relationships between our main variables: bank inefficiency and bank risk. In this way, it is possible to have one-way causality, i.e. running from inefficiency to distance to default or vice versa, but also a bi-directional one.

To address a common issue that emerges in panel-VAR analysis concerning the heterogeneity across banks (see Arellano and Bover, 1995) we set individual specific terms. In detail, our panel-data VAR allows for unobserved individual heterogeneity (Love and Zicchino, 2006). We specify a first order VAR model as follows:

$$w_{it} = \mu_i + \Phi w_{it-1} + e_{i,t}, \quad i = 1,\ldots, \mathrm{N}, \; t = 1,\ldots,\mathrm{T}. \qquad (7)$$

where w_{it} is a vector of two random variables, inefficiency and risk, Φ is an 2x2 matrix of coefficients, μ_i is a vector of m individual effects and $e_{i,t}$ is a multivariate white-noise vector of m residuals. As with standard VAR models, all variables depend on lags, the main difference lies in the presence of the individual specific terms μ_i.[7] Regarding estimation and inference, we use a system-based GMM estimator for each equation as in Arellano and Bover (1995). Moreover, we obtain parameters by regressing the endogenous variables on the whole set of lagged endogenous variables. The above system of equations is in reduced form, so that once estimated it can be used to implement dynamic simulations. This analysis involves the estimation of impulse response functions (IRF) and variance decompositions (VDC) and requires solving a complex identification problem. A commonly used way to tackle this problem is to opt for a preference ordering so as to satisfy that more exogenous variables impact on the more endogenous ones in a sequential order (see Love and Zicchino, 2006; Arias and Escudero, 2007). This is the standard identification strategy implicit in the Choleski decomposition, which induces a recursive orthogonal structure on the structure of the shocks $e_{i,t}$. In this paper we make the plausible assumption that risk, measured by the distance to default and derived from a Merton's options pricing model, could be *'relatively'* more exogenous than efficiency. Thus, in the model with two variables we assume that the lagged distance to default would affect inefficiency. The reverse causation will also be tested. [8]

---

[7] In order to impose that the underlying structure is the same for each cross-sectional unit we allow for '*individual heterogeneity'* in the levels of the variables by introducing fixed effects, denoted by μ_i as in Love and Zicchino (2006). In addition, the fixed effects are correlated with the regressors due to lags of the dependent variables and as a result the mean-differencing procedure commonly used to eliminate fixed effects would create biased coefficients. To avoid this problem we use forward mean-differencing, also referred to as the *'Helmert procedure'* (Arellano and Bover, 1995). This procedure removes only the forward mean, i.e. the mean of all the future observations available for each firm-year. This transformation preserves the orthogonality between transformed variables and lagged regressors, so that we can use lagged regressors as instruments and estimate the coefficients by system GMM.

[8] Note, though, that the ordering would be irrelevant if there are low estimated covariances between the errors across equations. Preliminary results show that indeed these covariances are low.

In detail, we model inefficiency and distance to default in two-equations VAR with the following structure:

$$
\begin{aligned}
I_{it} &= \mu_{1i0} + \mu_{10t} + \sum_{j=1}^{J} a_{11} I_{it-j} + \sum_{j=1}^{J} a_{12} DD_{it-j} + e_{1i,t} \\
DD_{it} &= \mu_{2i0} + \mu_{20t} + \sum_{j=1}^{J} a_{21} I_{it-j} + \sum_{j=1}^{J} a_{22} DD_{it-j} + e_{2i,t}
\end{aligned}
\qquad (8)
$$

Here, I_{it} and DD_{it} capture the bank inefficiency and distance to default respectively, while μ_{i0} and μ_{0t} are industry and time dummies, respectively.[9]

4. Data sources and data description

Our data comprises of listed banks in the 27 Member States of the European Union over the period 1998 to 2006. The number of listed banks varies widely across countries, ranging from 1 in Estonia to 40 in Denmark. Balance-sheet and income statement data were obtained from the Bankscope database[10], while data on macroeconomic and banking variables were collected from the World Development Indicators Database and from European Central Bank reports. For the estimation of bank default risk, stock price data were obtained from Datastream, Bloomberg and Bankscope databases. After reviewing the data for reporting errors and other inconsistencies, we obtain an unbalanced panel dataset of 1,653 observations, which includes a total of 251 different banks.[11]

[9] A more detailed analysis of the panel-VAR model is provided in the Appendix.
[10] The Fitch-IBCA Bankscope database is a comprehensive database that allows cross country comparisons, as it collects data from the banks' balance sheet, income statement and related notes found in audited annual reports and converts them to a "global format" which is a standardized template derived from country specific templates (Claessens et al., 2001). In this way, differences in reporting and accounting conventions across countries are taken into account allowing for cross-country comparisons.
[11] Bankscope database sometimes reports both consolidated and unconsolidated data for some banks. However, the most common format is unconsolidated data. As a result, we use only the variables for the U1 code (unconsolidated statement). In addition, the same bank sometimes appeared in the original Bankscope database more than once due to the application of different accounting standards. In such a case, we use variables based on

For the definition of bank inputs and outputs, we employ the intermediation approach proposed by Sealey and Lindley (1977), which assumes that banks collect funds, using labour and physical capital, to transform them into loans and other earning assets. [12] In particular, in order to measure productive efficiency, we specify three inputs, labour, physical capital and financial capital, and two outputs loans, and other earning assets.[13] Due to lack of data on the number of employees, labour is measured by personnel expenses, while physical capital is defined as the bank's fixed assets. Loans are expressed as total loans net of provisions, while other earning assets include government securities, bonds, equity investments, CDs, T-bills, equity investment etc. In addition, for the estimation of cost and alternative profit efficiency, input prices are required. The price of financial capital is computed by dividing total interest expenses by total interest bearing borrowed funds, while the price of labour is defined as the ratio of personnel expenses to total assets. In the case of cost and profit function, physical capital is specified as a fixed netput. Total cost is defined as the sum of overheads (personnel and administrative expenses), interest, fee, and commission expenses, while profit is defined as profit before tax.

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the international accounting standards (IAS). Furthermore, the fact that we had to combine three different databases (Bankscope, DataStream and Bloomberg) to form our dataset, helped us to avoid any double counting.

[12] A variety of approaches have been proposed in the literature for the definition of bank inputs and outputs. These include the intermediation (or the asset) approach, the production, the value-added and the user-cost approach (see Berger and Humphrey, 1992; Maggi and Rossi, 2003). Berger and Humphrey (1997) and Yildirim (2002) argue that the intermediation approach may be more appropriate when studying the economic viability of banks as it incorporates the overall costs of banking. Since our main interest lies in the assessment of overall efficiency and economic viability of banks and its relationship with default risk, the *intermediation approach* seems to fit better the purposes of our analysis.

[13] Note that recent studies in the literature (Clark and Siems, 2002; Isik and Hassan, 2002; Casu and Girardone, 2005), as a Referee pointed out, introduce off-balance-sheet activities as an additional output, since some of these activities could affect the efficiency measures. However, the IBCA database does not provide detailed information about off-balance sheet activity. In addition, Becalli et al., (2006) argue that the great variability in accounting practices across countries, especially with respect to the treatment of off-balance-sheet activities, may introduce a remarkable sample bias if off-balance-sheet data are used in cross country studies.

In estimating both the directional distance function and the cost and profit functions, we include equity capital as a quasi-fixed input.[14] If financial capital is ignored, the efficiency of banks that may be more risk averse than others and may hold a higher level of financial capital would be mismeasured, even though they are behaving optimally given their risk preferences.[15] Apart from this, a bank's capital directly affects costs by providing an alternative to deposits as a funding source for loans (Berger and Mester, 1997).

We also include several control variables in order to allow for the effect of country features in the case of the cost and profit functions. These variables are: the Herfindahl Index to measure concentration, the ratio of non-performing loans to total loans to control for differences in banks' loan quality, the share of foreign-owned banks assets as a percentage of total banking assets, the capitalization ratio to control for the part of risk that is attributed to the overall system, the interest rate spread, which is used as a proxy for competition for banking services, the logarithm of total assets to control for size effects, the ratio of bank liquid assets to total assets at the country level to capture liquidity risk, the intermediation ratio, a measure of branch density and two macroeconomic variables, that is GDP per capita and inflation, to control for differences in the macroeconomic environment across countries.[16]

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[14] In the case of the directional distance function, equity capital enters the function with a directional vector value set to zero.

[15] Hughes and Moon (1995) and Hughes et al. (1996) tested and rejected the assumption of risk neutrality for banks.

[16] The Herfindahl Index is defined as the sum of the square of banks' market shares in terms of assets in each country. The interest rate spread is defined as the difference between the annual average country-level lending rate minus deposit rate. The intermediation ratio is defined as the country's ratio of total loans to total deposits, while branch density is defined as the number of branches per square kilometre. Descriptive statistics of all the variables are available upon request.

The distance to default is derived from the market value of a risky debt (Merton, 1974), based on the Black and Scholes (1973) option pricing theory and measures the number of standard deviations away from default.[17] For the computation of bank default risk, we estimate the annual equity volatility for each bank, based on daily returns, derived as the standard deviation of the moving average of daily equity returns times $\sqrt{261}$. All liabilities are assumed to be due in one year, T=1, while as risk free interest rate we take the twelve months interbank rates, except for a few countries (Greece, Estonia, Lithuania), for which we opt for the six month interbank rate due to data availability. Liabilities are derived from Bankscope Fitch IBCA and include the total amount of deposits, money market funding, bonds and subordinated debt.

5. Empirical results

5.1 Efficiency results by country

Table A1 in the Appendix presents the estimated parameters of the directional distance function as well as the cost and profit functions as derived under a Stochastic Frontier Approach and shows that most of the maximum likelihood coefficients in all three equations are statistically significant.[18] The estimates of λ for all three frontiers are higher than one, suggesting that technical inefficiency, as identified within the

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[17] The main determinants of the distance to default are: the market value of the bank assets, the asset risks and leverage. Based on Merton (1974) the market value of a bank's assets follows a stochastic process that is a geometric Brownian motion with a drift: $dMV_B = \mu MV_B dt + \sigma_B MV_B dz$, where MV_B and dMV_B is the bank's asset value and change in the asset value respectively, μ, σ_B is the bank's asset value drift and volatility, while dz is a Wiener process. The drift can be approximated by the risk free interest rate. Bank liabilities consist of the debt (D) and equity (E), and thus the market value of equity (MV_E) is defined as: $MV_E = MV_E N(d_1) - De^{-rT} N(d_2)$, where $d_1 = \frac{\ln(\frac{MV_B}{D}) + (r + \frac{\sigma_B^2}{2})}{\sigma_B \sqrt{T}}$, $d_2 = d_1 - \sigma_B \sqrt{T}$, with r being the risk free interest rate. It can be shown that the volatility of equity and market value of bank are related as follows: $\sigma_E E_0 = N(d_1)\sigma_B B$. Solving for MV_B and σ_B, the distance to default is then defined as: $DD = \frac{\ln(\frac{MV_B}{D_t}) + (\mu - \frac{\sigma_B^2}{2})t}{\sigma_B \sqrt{T}}$

[18] In order to check for potential multicollinearity correlations among the independent variables of Eq. (6) we calculated variance inflation factors (VIFs) for all control variables specified. Results are available upon request and indicate no multicollinearity problem.

composite error term, plays an important role in the analysis of bank performance. The one-sided generalized likelihood ratio tests indicate that λ is statistically significant, thus confirming the importance of technical inefficiency effects. Table 1 presents cost, profit and productive inefficiency scores for each country and for the EU-27 banking industry as a whole.[19] Consistent with the literature, the overall results highlight that in general the inefficiency values derived from cost, profit as well as the directional distance functions are fairly high, indicating that banks operate far from the efficient frontier.

(Please insert Table 1 about here)

In the case of productive efficiency, industry inefficiency is measured as the sum of the individual bank directional distance function estimates. Consistent aggregation from banks to industry is facilitated by the use of a 'constant' direction vector. For comparison purposes across countries the figures have been adjusted for the number of banks operating in each country at each time period. It should be noted that this measure of inefficiency is based on the directional technology distance function and not on the traditional Shephard distance functions and thus, in this case a score of zero indicates that a bank is technically efficient. Table 1 shows that the average inefficiency score derived from the directional distance function is estimated at 0.723, ranging from 0.18 in Malta to 3.56 in the Netherlands.

Cost and profit inefficiency results also highlight the presence of a substantial level of inefficiency in the banking systems of the EU-27 countries. In line with previous evidence (i.e. Berger and Mester, 1997; Berger et al., 2000), estimated profit

[19] As pointed out by an anonymous referee, note that our efficiency estimates, which are based on unconsolidated data, due to data availability, relate to subsidiaries of banking organizations in each country and do not take explicitly into account the way the production is organized at the conglomerate level. Berger et al. (2000) argue that despite the fact that it is not possible to determine the extent to which transfer pricing, shared inputs, and other intra-organizational arrangements might impact efficiency assessments, most evidence suggests that any potential bias is very small.

inefficiency is higher than cost inefficiency. In particular, we observe an average profit inefficiency score of 0.37, compared to a mean cost inefficiency estimate of 0.24, suggesting that there are significant inefficiencies on the revenue side. Looking at the average country-level inefficiency scores reveals considerable variation in bank performance across countries, especially in the case of profit efficiency. More specifically, profit inefficiency ranges from 0.287 in Cyprus to 0.512 in the UK. On the other hand, cost inefficiency scores show a higher degree of homogeneity across countries, ranging from 0.207 in the Czech Republic to 0.355 in Hungary, with the majority of the countries clustering around 0.20 to 0.25.

Examining the rank-order correlations between the three alternative efficiency concepts reveals some interesting results. The rank-order correlation between cost and profit inefficiency scores is estimated at about 0.57. On the other hand, the rank order correlation between productive and cost inefficiency is much lower (0.30). Consistent with the fact that the directional distance function is dual to the profit function (Färe et al., 2007), the rank-order correlation between productive and profit inefficiency is much higher, estimated at 0.55.

(Please insert Figure 1 about here)

Regarding the evolution of inefficiency scores over time for our entire sample (see Figure 1) diverging trends are observed across the three alternative inefficiency concepts. Cost inefficiency exhibits a rather stable pattern over the examined period. On the other hand, profit inefficiency after an initial decline up to 1999, presents an upward trend until 2002 then declines somewhat before turning upwards again reaching its highest average value in the last year. In the case of productive inefficiency, an upward pattern is much more evident. With the exception of the subperiod 2001-2003, when a downward trend is observed, productive inefficiency increases over the examined period. As far as the evolution of inefficiency scores at the country level is concerned, different patterns can be observed across EU banking systems.[20] In particular, in the case of productive efficiency Romania, Greece and the Czech Republic show the largest improvement over the examined period, while on the other hand the UK, Belgium and the Netherlands exhibit a deteriorating productive efficiency over time.[21] In terms of cost efficiency, the largest improvements are observed in the case of Latvia, Luxembourg and Slovakia, while Bulgaria on the other hand presents a clear downward trend in its average cost efficiency score over time. Finally, in the case of profit efficiency, Czech banks increase their average profit efficiency over the examined period, while Finish and UK banks follow the opposite trend.

5.2 Efficiency results by type of ownership

We divide banking institutions into two categories; majority domestic owned (domestic investors, either private or government, hold more than 50% of equity) and foreign owned (foreign owners hold more than 50 per cent of the shares) banks.[22] Table 2 presents inefficiency estimates of banks with different ownership structure.

(Please insert Table 2 about here)

[20] Results are not shown, but can be provided by the authors upon request.

[21] This result is of some significance as the recent bank crisis appears to have severely affected the UK, Belgium and the Netherlands.

[22] As the Bankscope database reports ownership information only for 2006, we follow Bonin et al. (2005) and assume that the ownership status of each bank has remained unchanged during the examined period. If the percentages in the data do not add up to 100 per cent, we infer the characteristics of the remaining owners, as we are interested only in the type of the majority owner. If there is no majority owner and the stakes do not add up to 100 per cent, we assume that there are unreported domestic private owners as long as some private ownership is indicated. If no private ownership is indicated, we attribute the residual to the largest category of owners reported. In this way, we allocate 100 per cent of the banks shares to foreign or domestic owners for each observation (Bonin et al., 2005). Our initial aim was to divide banks into three mutually exclusive categories, that is, foreign, state-owned and domestic private banks. However, due to the small number of listed state-owned banks in our sample, we had to merge state-owned and domestic private banks into one category (domestic banks).

Our results suggest that foreign banks are on average more productive efficient than domestic banks, consistent with the *global advantage* hypothesis which argues that efficient foreign institutions with superior managerial skills or best-practice policies are able to overcome any cross-border disadvantages and operate abroad more efficiently than domestic institutions (Berger et al., 2000). On the other hand, both foreign and domestic banks exhibit similar levels of profit inefficiency, while in terms of cost, domestic banks slightly outperform their foreign competitors, indicating that the latter may face some organizational disadvantages that are manifested as higher costs in providing the same financial services. This could be consistent with the *home field advantage* hypothesis, stating that domestic institutions are generally more efficient than foreign institutions due to organizational diseconomies the latter face to operating or monitoring an institution from a distance (Berger et al., 2000). Overall, our findings present a variety of results regarding the relationship between ownership structure and inefficiency. This could be attributed to the fact that our sample includes both developed and developing economies. In order to shed more light on this issue, the following section provides additional evidence on the potential efficiency differences between high and low financial development countries.

5.3 Efficiency results by level of financial development

We divide our sample into two groups of countries on the basis of the level of financial development and estimate inefficiency scores based on separate frontiers. In order to do so, we construct an index of financial development (FD), by combining standardised measures of five indicators proposed by Demirguc-Kunt and Levine (1996): market capitalisation over GDP, total value of traded stocks over GDP, turnover ratio, domestic credit to the private sector as a percent of GDP and interest spread. We split countries into two groups based on the median of this indicator.[23] We refer to these two groups as *'high'* financial development (HFD) countries and *'low'* financial development (LFD) countries. Nevertheless, we should note that this distinction is relative, as it is based on the median level of financial development among countries in our sample.

Table 3 presents the results for cost, profit and productive inefficiency for high and low financial development countries, based on separate frontiers. A direct comparison of inefficiency scores under separate frontiers is not meaningful; nevertheless, some interesting findings arise when comparing the average scores across the two samples. Both groups of countries exhibit similar levels of average cost inefficiency, while on the other hand low financial development countries outperform high financial development countries in terms of profit and productive efficiency. The better performance of low financial developed countries is much more evident in the case of productive efficiency. A possible explanation is that banks in low financial development countries that are listed in stock exchanges are usually the largest and best performing banks in their countries. Moreover, given that banks in low financial development play a central role in financial intermediation and in the provision of funds to the economy, they may have some degree of market power and thus earn higher profits.

(Please insert Table 3 about here)

Among the low financial development countries Estonia appears to be the most cost and profit efficient, while Hungary is the worst performer. In terms of productive efficiency, Slovakia outperforms all low financial development countries, while

[23] Given that our sample consists of 27 countries, our sample is split into two unequal subgroups. We arbitrarily chose to place Belgium, which had the median FD index, to the category of low financial development countries, as this subgroup has the lowest number of observations.

Belgium ranks at the bottom of the list. Looking at the high financial development countries, Cyprus presents the lowest cost and profit inefficiency scores, while Ireland and the UK report the highest scores both in terms of cost and profit efficiency, respectively. Moreover, Denmark exhibits the lowest productive inefficiency score, while Netherlands and the UK the highest ones.[24] As one would expect, when estimating separate frontiers for high and low financial development countries, cost, profit and productive inefficiency scores in both samples are lower when compared to the common frontier. This could indicate that separate frontiers are better able to capture the underlying frontier. However, the rank-order correlation between the common and separate frontiers is high, especially in the case of profit inefficiency.

5.4. Panel VAR Analysis

Prior to the estimation of the panel VAR we have to decide the optimal lag order *j* of the right-hand variables in the system of equations (Lutkepohl, 2006). To do so, we opt for the Arellano-Bover GMM estimator for the lags of j=1,2 and 3. Results are reported in Table A2 in Appendix. We use the Akaike Information Criterion (AIC) to choose the optimal lag order. The AIC suggests that the optimum lag order is one, while the Arellano-Bond AR tests confirm this. To test for evidence of autocorrelation, more lags were added. The Sargan tests show that for lag order one, we can not reject the null hypothesis. Therefore, we choose VAR of order one. The lag order of one preserves degrees of freedom and information given the low time frequency of our data. In addition, we perform normality tests for the residuals, opting for the Sahpiro-Francia W' test. Our results do not show violation of the normality.

[24] These results further confirm our previous findings regarding the implications of the bank crisis in Belgium, UK and Netherlands.

Moreover, to analyze the impulse-response functions we need an estimate of their confidence intervals. We calculate standard errors of the impulse response functions with Monte Carlo simulations and generate confidence intervals.[25] Monte Carlo simulations method essentially randomly generates a draw of coefficients of the VAR using the estimated coefficients and their variance covariance matrix to re-calculate the impulse responses (see Love and Zicchino, 2006).

Next we report the parameter estimates of the system of equations for cost, profit and productive inefficiency, as well as for the distance to default (see Table 4). The results show that the impact of distance to default on inefficiency is negative and significant for all three different panel VARs. On the other hand, the impact of inefficiency on the distance to default is negative in the case of cost and profit inefficiency, but positive in the case of productive inefficiency, yet in all cases these impacts are not significant.

(Please insert Table 4 about here)

One might question whether these findings are meaningful. Love and Zicchino (2006) argue that one should direct the attention to the underlying moving average (MA) representation of the VAR model and the resulted impulse response functions (IRFs) and variance decompositions (VDCs). To determine this, we report next the IRFs and VDCs.

[25] This procedure can be repeated thousand times. In this paper we repeat the procedure up to 5000 times to make sure that results are similar. Then, the 5th and 95th percentiles of this distribution is generated and used as a confidence interval for the impulse responses.

5.4.1. IRFs and VDCs for productive, cost and profit inefficiency

The IRFs derived from the unrestricted Panel-VAR are presented in diagrams below. More precisely, diagrams report the response of each variable of the VAR analysis (inefficiency and distance to default) to its own innovation and to the innovations of the other variable. Figure 2 presents the results for the case of productive inefficiency, as derived from the directional technology distance function.

(Please insert Figure 2 about here)

From the first row of Figure 2 it is clear that the effect of a one standard deviation shock of distance to default on inefficiency is negative and large in magnitude, though the confidence interval becomes wider after two years. The peak response of inefficiency to a shock in the distance to default takes place after three years, while it converges towards the equilibrium thereafter.[26] A shock in the distance to default that would increase the distance to default, and thus lower the risk, reduces productive inefficiency by 0.25 in the short run of the first two years. Effectively this outcome would suggest that the causal relationship runs from distance to default to productive inefficiency and carries a negative sign, consistent with Hypothesis 1, that is, the *'bad luck'* or the *'efficient market'* hypotheses.

This result has some important policy implications especially in light of the recent financial turmoil. Our findings indicate that banks in a perilous financial situation whether because of *'bad luck'* or adverse economic external effects, such as severe economic slowdowns, would face dear costs in order to defend their safety and soundness record to bank supervisors and market participants alike. These soaring costs, caused by an increase in bank default risk, would trigger an increase in bank

[26] Note, that where confidence interval of IRFs is wide one needs to treat results with caution. In our case this takes place after two periods.

inefficiency impeding further the stability of the market. A prudent policy response on behalf of bank regulators and supervisors would be to intensify their efforts so as to ensure that banks reduce their exposure to risk activities that in turn it would also lead to a reduction in the inefficiency. Such efforts may involve containing loan concentration and promoting product diversification (Lepetit et al., 2008).

Regarding evidence for the existence of a reverse causation, it is striking that although the response of the distance to default to inefficiency innovation is negative for the first year, then it turns into positive, before converging to zero after three years. This result hints at the complexities involved in the interaction between risk and inefficiency. In particular, it implies that this relationship might be positive after the first year with the causality running from inefficiency to risk. This result is in line with Hypothesis 4, the *'risk-averse management'* hypothesis. According to this hypothesis, European bank managers could allocate more inputs in the production of the same quantity of outputs, deteriorating their bank productive inefficiency scoring, though this would result in lower risk. However, note that the magnitude of the positive response of the distance to default to a shock in productive inefficiency is small with wide confidence intervals, while it is negative in the first two years, consistent with the '*bad management'* hypothesis.

To shed more light into our analysis, we also present variance decompositions (VDCs), which show the percent of the variation in one variable that is explained by the shock in another variable. We report the total effect accumulated over 10, 20 and 30 years in Table 5. These results provide further light to IRFs, insinuating the importance of risk in explaining the variation of inefficiency. Specifically, close to

13% of inefficiency's forecast error variance after thirty years is explained by distance to default's disturbances. On the other hand a small part, less than 1.5%, of the variation of distance to default is explained by inefficiency. This result implies that causality would run from risk to inefficiency, in line with *"bad luck"* Hypothesis 1.

(Please insert Table 5 about here)

Turning to the cost and profit efficiency results, Figure 3 presents IRFs. The first row confirms our previous evidence that the effect of a one standard deviation shock of the distance to default on cost inefficiency is negative, though the confidence interval is wide. The peak response of inefficiency to the distance to default takes place after three years, and converges towards the equilibrium thereafter. On the other hand the response of the distance to default to cost inefficiency's innovation is estimated equal to zero for the whole period. This result would imply that a causal relationship from risk to inefficiency may exist, consistent with Hypothesis 1, though this relationship is of a much smaller magnitude than in the case of productive efficiency.

Figure 3 further shows that the response of profit inefficiency to distance to default's innovations is also negative. The magnitude of this response is much smaller than in the case of both productive and cost inefficiency, as it is estimated at 0.02 over the first year, though for the first period the confidence interval is narrow. The reverse causation is also observed as the response of the distance to default to a shock in profit inefficiency is negative for the first two periods while it converges to zero thereafter. This last finding provides some evidence in favour of Hypothesis 2. In this respect, it may possible that, where profit inefficiency matters, while the relationship between inefficiency and the distance to default keeps its negative sign, it could be a case of a bi-directional causality as both *"bad luck"* and *"bad management"* hypotheses may be at play. Given that both hypotheses are closely related, predicting a negative relationship between the distance to default and inefficiency, differing only in the direction of causality, this bi-directional causality may not seem quite as odd as at a first sight.

(Please insert Figure 3 about here)

Table 5 also presents the VDCs estimations for the cost and profit functions. These results provide further evidence favouring the importance of risk in explaining the variation of inefficiency. More specifically 5% of cost inefficiency's forecast error variance after thirty years is explained by distance to default's disturbances. On the other hand a very small part of the variation of distance to default is explained by cost inefficiency. In the case of profit inefficiency, VDCs show that 13% of the forecast error variance of the profit inefficiency is explained by disturbances in the distance to default, while only 1% of the forecast error variance of the distance to default is explained by disturbances in the profit inefficiency. To this end, VDCs strongly show that Hypothesis 1 could be valid.

5.4.2 Sensitivity analysis: IRFs and VDCs for domestic vs. foreign owned banks

Next, Figure 4 reports the IRFs for domestic and foreign banks in the case of productive inefficiency. Note that for domestic banks, estimations show IRFs consistent with Hypothesis 1. In particular, the effect of distance to default shocks on productive inefficiency is found to be negative and large in magnitude, while the reverse causation is observed only for a very short time period, less than a year. Approximately the response of inefficiency to a one standard deviation shock of distance to default is close to 0.32. For the case of foreign banks, the response of inefficiency to shocks to distance to default appears to take a zero value. This difference between domestic and foreign banks shows that ownership structure affects the interaction between risk and efficiency.

(Please insert Figure 4 about here)

VDCs estimations are presented in Table 6 and broadly confirm previous findings. Specifically, 17% of productive inefficiency's forecast error variance of domestic banks after thirty years is explained by distance to default's disturbances, while only 1% of the variation of distance to default is explained by productive inefficiency. On the other hand, in the case of foreign banks, VDCs report that only 2% of productive inefficiency's forecast error variance after thirty years is explained by distance to default's disturbances, while also small part of the variation of distance to default is explained by productive inefficiency, 6%.

(Please insert Table 6 about here)

Next we report the IRFs for cost and profit inefficiency (see Figure 5). Clearly for domestic banks the impact of a one standard deviation shock of distance to default on inefficiency is negative in the case of both cost and profit inefficiency, consistent with Hypothesis 1, though small in magnitude especially in the cost inefficiency case. On the other hand, in the case of profit inefficiency we observe reverse causation, as the response of the distance to default to inefficiency's innovation is negative. This is consistent with Hypothesis 2. These findings would imply that when the ownership of the bank is domestic the causal relationship may run from the risk measure to inefficiency, while some reverse causation can not be excluded for a short period of time. For foreign banks, the impact of a shock in the distance to default on cost and profit inefficiency is negative, though small in magnitude, whereas the response of distance to default to both cost and profit inefficiency shocks is zero.

(Please insert Figure 5 about here)

VDCs show that 12% and 7% of profit and cost inefficiency's forecast error variance respectively after thirty years is explained by distance to default's disturbances for domestic banks (see Table 6). For foreign banks, 16% and 6% of profit and cost inefficiency's forecast error variance respectively after thirty years is explained by distance to default's disturbances. On the other hand, a very small part of the variation, around 1%, of the distance to default is explained by inefficiency for both types of ownership. Thus, the VDCs results would also imply that the causality would run from bank risk to inefficiency for both domestic and foreign banks.

5.4.3 Sensitivity analysis: IRFs and VDCs for high level financial developed vs. low financial developed banks

This section presents evidence of IRFs and VDCs for countries with a different level of financial development. For high financial developed countries Figure 6 presents results consistent with Hypothesis 1. In particular, the effect of a shock in the distance to default on productive inefficiency is negative and large in magnitude. Approximately, the response of inefficiency to a one standard deviation shock of distance to default is close to 0.21 per annum. The reverse causation is small and it lasts only for the first year.

(Please insert Figure 6 about here)

For the case of low level financial developed countries the response of inefficiency on shocks of distance to default appears of some interest as it takes small, albeit positive, values for a short time period. This is interesting as it shows that for low financial development countries an increase in the distance to default would cause an increase in the productive inefficiency in the first year, converging to zero thereafter. This result resembles '*moral hazard'* hypothesis and the *'skimping'* hypothesis with the causality running from the distance to default to inefficiency.

VDCs estimations are presented in Table 7. Specifically, in the case of high financial development counties 20% of productive inefficiency forecast error variance after thirty years is explained by distance to default's disturbances. In the case of low financial development countries VDCs estimations are close to 30%. On the other hand, a very small part of the variation of distance to default is explained by inefficiency both for low and high financial developed countries.

(Please insert Table 7 about here)

Regarding cost and profit inefficiency the IRFs presented in Figure 7 show that the impact of a one standard deviation shock of distance to default on cost and profit inefficiency is clearly negative in the case of high level financial developed countries. The peak response of inefficiency to risk takes place after two years and converges towards the equilibrium thereafter. On the other hand, the response of distance to default to inefficiency's innovation is estimated close to zero for the whole period, although in the case of profit inefficiency there is evidence of a small negative response in the first year. These results confirm previous findings that the causal relationship would run from bank risk to inefficiency. For low financial development countries the response of cost inefficiency to a shock in the distance to default is small but positive for the first year, while it takes negative values for the subsequent three years before converging to zero. On the other hand, the response of profit inefficiency to a shock in the distance to default is negative. This provides evidence that the causality could run from the distance to default to inefficiency for low financial development countries. However, in the case of profit inefficiency the reverse causality, from inefficiency to the distance to default, is evident, while the confidence interval is narrow. This result is consistent with Hypothesis 2, insinuating that Hypotheses 1 and 2 are closely related.

(Please insert Figure 7 about here)

Table 7 also presents the VDCs estimations for the cost and profit functions, which provide further evidence favouring the importance of risk in explaining the variation of inefficiency. Specifically, in the case of high financial development countries, 2% to 5% of inefficiency's forecast error variance of cost and profit inefficiency respectively after thirty years is explained by distance to default's disturbances. On the other hand, in the case of low financial development countries a considerable part of the variation of distance to default is explained by cost inefficiency. In detail, 11% of the forecast error variance of distance to default is explained by shocks in the cost inefficiency, dropping to 5% in the profit inefficiency case. These results provide some indications that in the case of low financial developed countries Hypothesis 2 of *'bad management'* could be valid. However, 16% of profit inefficiency's forecast error variance is due to the distance to default shocks, showing that the reverse causality, consistent with Hypothesis 1, is higher in magnitude.

6. Conclusions

The panel-VAR analysis performed in this study reveals some interesting findings regarding the dynamic interaction between efficiency and risk. In terms of causality, IRFs and VDCs show that in most cases risk causes inefficiency. The reverse causal relationship is not refuted, notably in the case of profit inefficiency, but evidence is weaker. As part of a sensitivity analysis, we also investigate the relationship between efficiency and default risk across banks with different ownership structures and across financial systems with different levels of development. Most IRFs show that causality runs form distance to default to inefficiency, and they share a negative relationship, though the reverse causality can not be excluded for some subsamples. In particular, in the case of foreign and domestic banks cost inefficiency may cause risk, consistent with the "*bad management*" hypothesis. This result also holds in the subsamples of low financial development countries and domestic banks in the case of profit inefficiency. Moreover, in the case of low financial development countries distance to default would positively affect productive inefficiency, a result that resembles *"moral hazard"* hypothesis.

Our analysis has important policy implications, and sheds some additional light on the existence or not of a trade-off between efficiency and financial stability. Assuming that bank distance to default is a measure of financial stability[27], we find evidence that a trade-off between efficiency and financial stability may not exist. The majority of our results clearly demonstrate that financial stability and efficiency are positively related and the causality runs from the former to the latter. Effectively, the distance to default may act as an early warning mechanism not only for financial instability, but also for inefficient operation. Therefore, monitoring the distance to default would enhance financial markets ability to be better prepared to deal with crises, but it would also improve their efficiency.

This finding has significant implications for regulators and supervisors, whose task is to establish a secure as well as an efficient financial system. Banks facing high risks whether because of adverse economic external effects such as severe economic

[27] A lower distance to default, or in other words higher default risk, would imply lower level of financial stability.

slowdowns, or bad management, would have to bear heightened costs, as a defensive response so as to improve their safety and soundness record to supervisors and market participants alike, that would reduce their efficiency in the short-run. A prudent policy advice would ask of banks, in particular those with a low distance to default, to intensify efforts to lower exposure to risky activities.

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Table 1: Inefficiency scores by country

	PrI		*CI*		*πI*		*DD*		*Obs*
	mean	st.dev.	mean	st.dev.	mean	st.dev.	mean	st.dev.	
Country									
Austria	0.307	*(0.304)*	0.245	*(0.133)*	0.348	*(0.156)*	14.799	*(3.770)*	57
Belgium	2.172	*(2.636)*	0.276	*(0.170)*	0.416	*(0.232)*	8.233	*(2.572)*	27
Bulgaria	0.193	*(0.033)*	0.336	*(0.169)*	0.324	*(0.138)*	4.935	*(0.706)*	4
Cyprus	0.186	*(0.039)*	0.209	*(0.048)*	0.287	*(0.084)*	7.215	*(2.582)*	20
Czech Republic	0.304	*(0.075)*	0.207	*(0.020)*	0.341	*(0.174)*	6.812	*(1.842)*	9
Denmark	0.233	*(0.331)*	0.216	*(0.064)*	0.334	*(0.132)*	11.892	*(2.892)*	333
Estonia	0.204	*(0.049)*	0.209	*(0.032)*	0.307	*(0.068)*	9.613	*(1.014)*	4
Finland	0.180	*(0.041)*	0.223	*(0.086)*	0.361	*(0.216)*	11.236	*(1.838)*	11
France	0.818	*(2.621)*	0.259	*(0.161)*	0.371	*(0.195)*	10.490	*(3.217)*	194
Germany	0.822	*(1.805)*	0.273	*(0.166)*	0.395	*(0.272)*	8.620	*(3.687)*	150
Greece	0.299	*(0.188)*	0.213	*(0.061)*	0.331	*(0.114)*	6.834	*(1.875)*	65
Hungary	0.242	*(0.063)*	0.355	*(0.189)*	0.408	*(0.291)*	7.354	*(1.700)*	17
Ireland	0.462	*(0.534)*	0.296	*(0.161)*	0.333	*(0.126)*	8.839	*(1.925)*	35
Italy	0.712	*(1.428)*	0.235	*(0.113)*	0.403	*(0.201)*	8.917	*(2.899)*	211
Latvia	0.184	*(0.038)*	0.253	*(0.156)*	0.358	*(0.171)*	7.570	*(2.366)*	7
Lithuania	0.192	*(0.037)*	0.218	*(0.072)*	0.371	*(0.153)*	7.596	*(2.472)*	29
Luxembourg	0.281	*(0.156)*	0.281	*(0.192)*	0.500	*(0.276)*	8.890	*(2.455)*	21
Malta	0.177	*(0.036)*	0.217	*(0.077)*	0.327	*(0.168)*	9.430	*(2.754)*	22
Netherlands	3.565	*(5.719)*	0.245	*(0.134)*	0.409	*(0.187)*	7.544	*(2.927)*	38
Poland	0.246	*(0.079)*	0.238	*(0.105)*	0.373	*(0.134)*	7.603	*(1.862)*	93
Portugal	0.307	*(0.251)*	0.216	*(0.069)*	0.357	*(0.148)*	10.095	*(2.516)*	42
Romania	0.277	*(0.141)*	0.218	*(0.068)*	0.336	*(0.146)*	6.767	*(2.306)*	11
Slovakia	0.199	*(0.037)*	0.246	*(0.126)*	0.360	*(0.173)*	9.040	*(3.179)*	20
Slovenia	0.188	*(0.039)*	0.216	*(0.077)*	0.332	*(0.118)*	10.789	*(3.036)*	7
Spain	0.771	*(1.675)*	0.212	*(0.056)*	0.348	*(0.155)*	10.439	*(2.733)*	77
Sweden	0.662	*(1.009)*	0.255	*(0.152)*	0.453	*(0.279)*	7.637	*(2.729)*	34
UK	2.399	*(5.330)*	0.261	*(0.142)*	0.512	*(0.345)*	8.529	*(2.394)*	115
EU-27	0.723	*(2.201)*	0.242	*(0.123)*	0.376	*(0.203)*	9.654	*(3.396)*	1,653

Note: The table presents mean values and standard deviations in parentheses. DD stands for distance to default, CI stands for cost inefficiency, πI is profit inefficiency, and PrI stands for productive inefficiency.

Table 2: Inefficiency scores by ownership

		Domestic	**Foreign**
PrI	mean	0.812	0.368
	st.dev.	*(2.432)*	*(0.661)*
CI	mean	0.237	0.260
	st.dev.	*(0.117)*	*(0.146)*
πI	mean	0.379	0.365
	st.dev.	*(0.206)*	*(0.190)*
DD	mean	9.974	8.266
	st.dev.	*(3.394)*	*(3.043)*
Obs		1,344	309

Note: The table presents mean values and standard deviations in parentheses. DD stands for distance to default, CI stands for cost inefficiency, πI is profit inefficiency, and PrI stands for productive inefficiency.

Table 3: Inefficiency scores –High financial development countries *vs.* Low financial development countries

	FD Index	PrI		CI		πI	
		mean	st.dev.	mean	st.dev.	mean	st.dev.
High Financial Developed Countries (HFD)							
Cyprus	0.590	0.073	*(0.009)*	0.121	*(0.021)*	0.161	*(0.030)*
Denmark	0.429	0.071	*(0.029)*	0.124	*(0.030)*	0.171	*(0.057)*
Finland	1.384	0.092	*(0.026)*	0.125	*(0.031)*	0.2	*(0.161)*
France	0.654	0.528	*(1.737)*	0.144	*(0.102)*	0.192	*(0.123)*
Germany	0.564	0.521	*(1.811)*	0.146	*(0.085)*	0.264	*(0.306)*
Ireland	0.268	0.314	*(0.253)*	0.163	*(0.118)*	0.169	*(0.055)*
Italy	0.268	0.288	*(0.713)*	0.133	*(0.070)*	0.205	*(0.139)*
Luxembourg	0.432	0.089	*(0.054)*	0.151	*(0.098)*	0.223	*(0.136)*
Netherlands	2.278	1.789	*(2.994)*	0.136	*(0.079)*	0.183	*(0.076)*
Portugal	0.322	0.113	*(0.139)*	0.124	*(0.030)*	0.174	*(0.062)*
Spain	1.999	0.376	*(0.883)*	0.123	*(0.026)*	0.171	*(0.061)*
Sweden	1.440	0.426	*(0.396)*	0.139	*(0.073)*	0.221	*(0.155)*
UK	2.183	1.308	*(2.836)*	0.148	*(0.088)*	0.323	*(0.293)*
HFD		0.448	*(1.486)*	0.137	*(0.072)*	0.204	*(0.169)*
Low Financial Developed Countries (LFD)							
Austria	-0.240	0.109	*(0.116)*	0.134	*(0.061)*	0.178	*(0.072)*
Belgium	-0.186	1.245	*(1.186)*	0.15	*(0.099)*	0.205	*(0.126)*
Bulgaria	-1.521	0.082	*(0.007)*	0.169	*(0.083)*	0.175	*(0.068)*
Czech Rep.	-0.695	0.134	*(0.053)*	0.119	*(0.011)*	0.173	*(0.067)*
Estonia	-0.957	0.196	*(0.014)*	0.119	*(0.009)*	0.166	*(0.037)*
Greece	-0.293	0.088	*(0.069)*	0.122	*(0.026)*	0.169	*(0.049)*
Hungary	-0.395	0.092	*(0.037)*	0.183	*(0.090)*	0.285	*(0.343)*
Latvia	-1.198	0.086	*(0.011)*	0.147	*(0.117)*	0.184	*(0.069)*
Lithuania	-1.303	0.075	*(0.008)*	0.126	*(0.034)*	0.173	*(0.052)*
Malta	-0.304	0.077	*(0.008)*	0.124	*(0.031)*	0.186	*(0.124)*
Poland	-1.173	0.077	*(0.040)*	0.135	*(0.072)*	0.175	*(0.057)*
Romania	-2.533	0.1	*(0.062)*	0.127	*(0.035)*	0.185	*(0.070)*
Slovakia	-0.851	0.074	*(0.012)*	0.132	*(0.051)*	0.181	*(0.076)*
Slovenia	-1.157	0.123	*(0.012)*	0.123	*(0.030)*	0.171	*(0.043)*
LFD		0.159	*(0.402)*	0.136	*(0.063)*	0.186	*(0.103)*

Note: The table presents mean values and standard deviations in parentheses. DD stands for distance to default, CI stands for cost inefficiency, πI is profit inefficiency, and PrI stands for productive inefficiency. FD Index is constructed based on the methodology of Demirguc-Kunt and Levine (1996).

Table 4: Panel VAR of a two variable model

Dependent variable	*CI_{-1}*	*DD_{-1}*	*Obs*
CI	0.53 (0.18)***	-0.028 (0.003)***	1141
DD	-0.32 (1.68)	0.47 (0.14)***	
	πI_{-1}	**DD_{-1}**	*Obs*
πI	0.20 (0.30)	-0.012 (0.004)***	1141
DD	-0.169 (3.73)	0.47 (0.17)***	
	PrI_{-1}	*DD_{-1}*	*Obs*
PrI	0.68 (0.07)***	-0.114 (0.04)***	1044
DD	0.14 (0.08)	0.421 (0.14)***	

Note: DD stands for distance to default, CI stands for cost inefficiency, πI is profit inefficiency, and PrI stands for productive inefficiency. The VAR models are estimated using GMM. Reported numbers show the coefficients of regressing the dependent variables on lags of the independent variables. Heteroskedasticity adjusted t-statistics are in parentheses. *** indicate significance at the 1% level.

Table 5: VDCs for productive cost and profit inefficiency

	s	PrI	DD		CI	DD		πI	DD
PrI	10	0.8701	0.1298	**CI**	0.9502	0.0498	**πI**	0.8668	0.1332
DD	10	0.0112	0.9888	**DD**	0.0003	0.9997	**DD**	0.0102	0.9898
PrI	20	0.8699	0.1300	**CI**	0.9502	0.0498	**πI**	0.8668	0.1332
DD	20	0.0111	0.9888	**DD**	0.0003	0.9997	**DD**	0.0102	0.9898
PrI	30	0.8699	0.1300	**CI**	0.9502	0.0498	**πI**	0.8668	0.1332
DD	30	0.0111	0.9888	**DD**	0.0003	0.9997	**DD**	0.0102	0.9898

Note: DD: distance-to-default, CI: cost inefficiency, πI: profit inefficiency and s notes the number of time periods ahead.

Table 6: VDCs for productive, cost and profit inefficiency: foreign vs. domestic

		Foreign		**Domestic**	
	s	**PrI**	**DD**	**PrI**	**DD**
PrI	10	0.97816	0.02185	0.82727	0.17273
DD	10	0.06339	0.93661	0.01037	0.98964
PrI	20	0.97816	0.02185	0.82717	0.17283
DD	20	0.06339	0.93661	0.01037	0.98963
PrI	30	0.97816	0.02185	0.82717	0.17283
DD	30	0.06339	0.93661	0.01037	0.98963
	s	**CI**	**DD**	**CI**	**DD**
CI	10	0.93896	0.06104	0.93214	0.06786
DD	10	0.00527	0.99473	0.00543	0.99457
CI	20	0.93896	0.06104	0.93191	0.06809
DD	20	0.00527	0.99473	0.00544	0.99456
CI	30	0.93896	0.06104	0.93191	0.06809
DD	30	0.00527	0.99473	0.00544	0.99456
	s	**πI**	**DD**	**πI**	**DD**
πI	10	0.83620	0.16381	0.87515	0.12485
DD	10	0.00686	0.99314	0.01265	0.98735
πI	20	0.83620	0.16381	0.87515	0.12486
DD	20	0.00686	0.99314	0.01265	0.98735
πI	30	0.83620	0.16381	0.87515	0.12486
DD	30	0.00686	0.99314	0.01265	0.98735

Note: DD: distance-to-default, CI: cost inefficiency, πI: profit inefficiency and s notes the number of time periods ahead.

Table 7: VDCs for productive inefficiency: High vs. Low financial developed countries

		Low-Financial Developed		High-Financial Developed	
	s	**PrI**	**DD**	**PrI**	**DD**
PrI	10	0.70048	0.29952	0.80419	0.19581
DD	10	0.06255	0.93745	0.00646	0.99354
PrI	20	0.70011	0.29989	0.79970	0.20030
DD	20	0.06256	0.93744	0.00651	0.99349
PrI	30	0.70011	0.29989	0.79969	0.20031
DD	30	0.06256	0.93744	0.00651	0.99349
	s	**CI**	**DD**	**CI**	dd
CI	10	0.99317	0.00684	0.98123	0.01877
DD	10	0.11282	0.88718	0.00003	0.99997
CI	20	0.99317	0.00684	0.98122	0.01878
DD	20	0.11282	0.88718	0.00003	0.99997
CI	30	0.99317	0.00684	0.98122	0.01878
DD	30	0.11282	0.88718	0.00003	0.99997
	s	**πI**	**DD**	**πI**	**DD**
πI	10	0.83949	0.16051	0.94958	0.05042
DD	10	0.05461	0.94539	0.01084	0.98916
πI	20	0.83944	0.16056	0.94958	0.05042
DD	20	0.05461	0.94539	0.01084	0.98916
πI	30	0.83944	0.16056	0.94958	0.05042
DD	30	0.05461	0.94539	0.01084	0.98916

Note: DD: distance-to-default, CI: cost inefficiency, πI: profit inefficiency and s notes the number of time periods ahead

Figure 1: Evolution of inefficiency over time

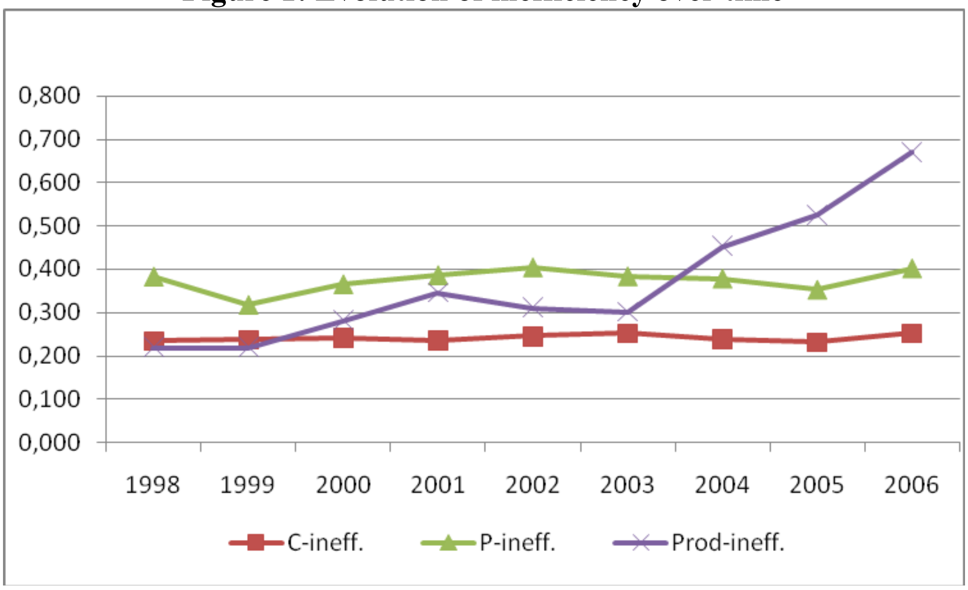
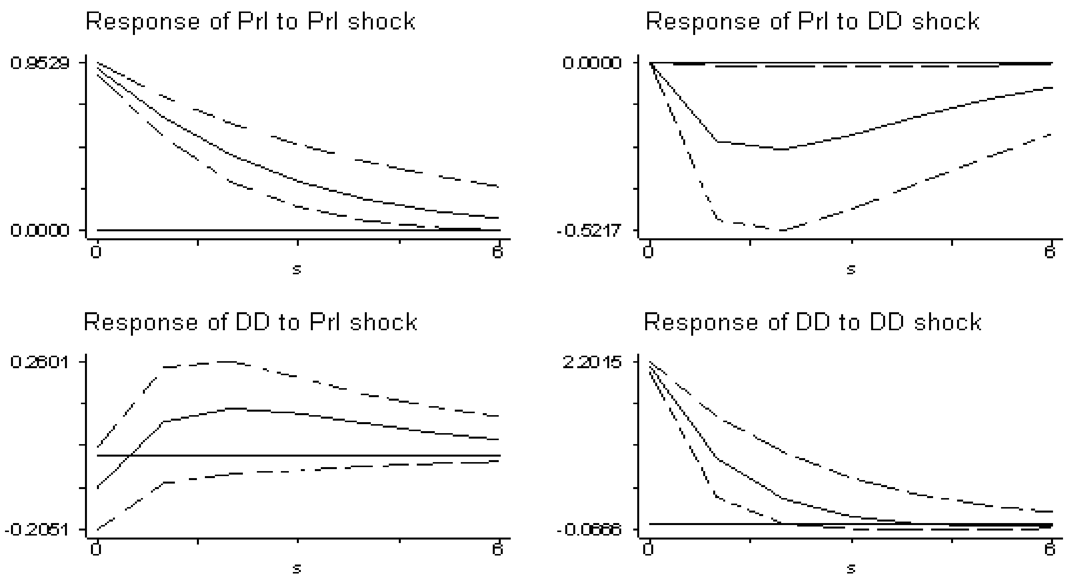


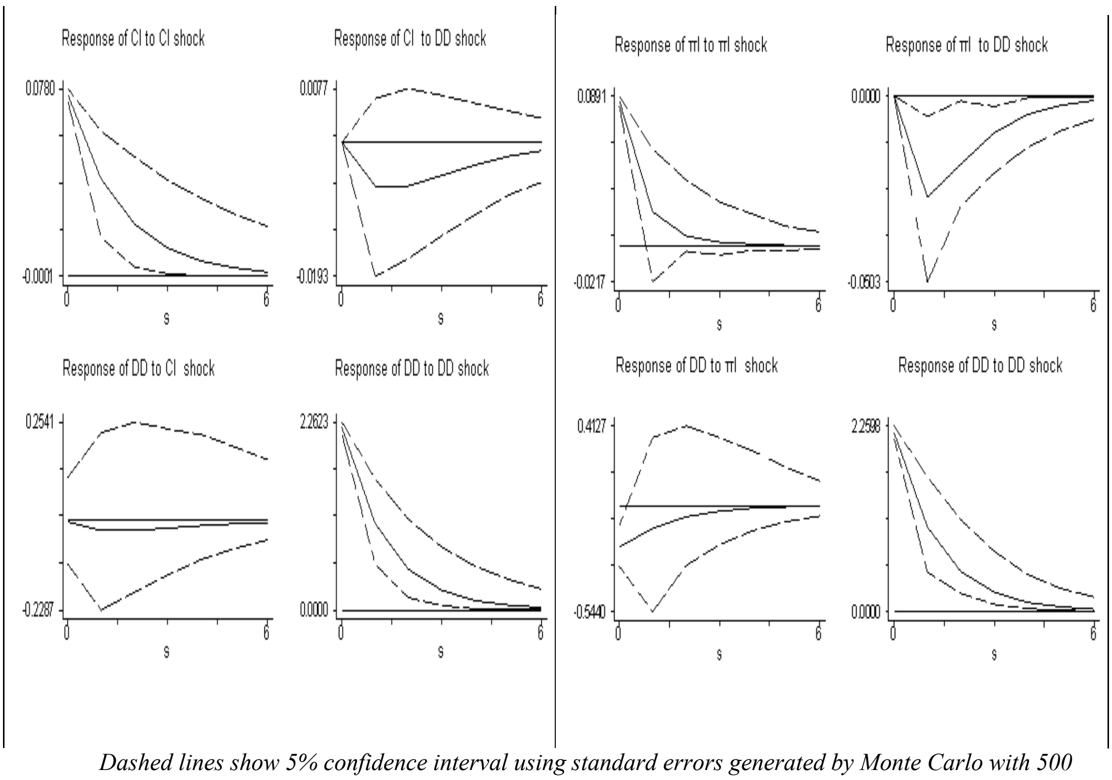
Figure 2: IRF for productive inefficiency (PrI) and distance to default (DD).



Dashed lines show 5% confidence interval using standard errors generated by Monte Carlo with 500 replications.

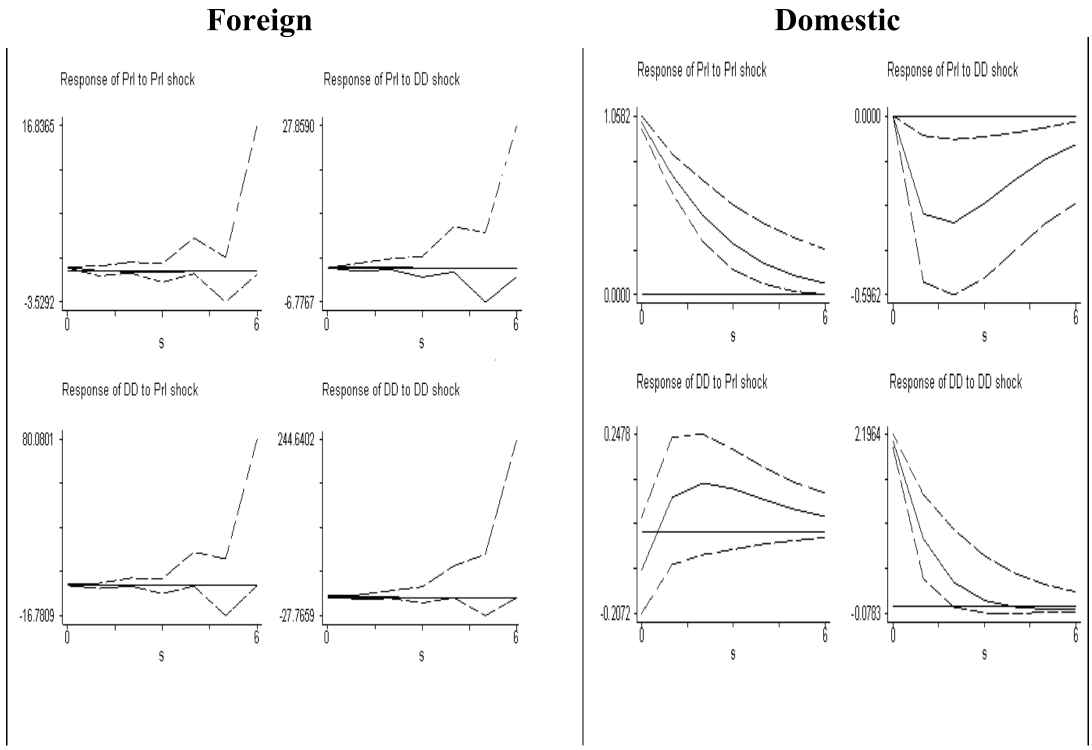
Figure 3: IRFs: CI, πI and DD.

CI and DD **πI and DD**



Dashed lines show 5% confidence interval using standard errors generated by Monte Carlo with 500 replications.

Figure 4: IRFs: PrI and the DD

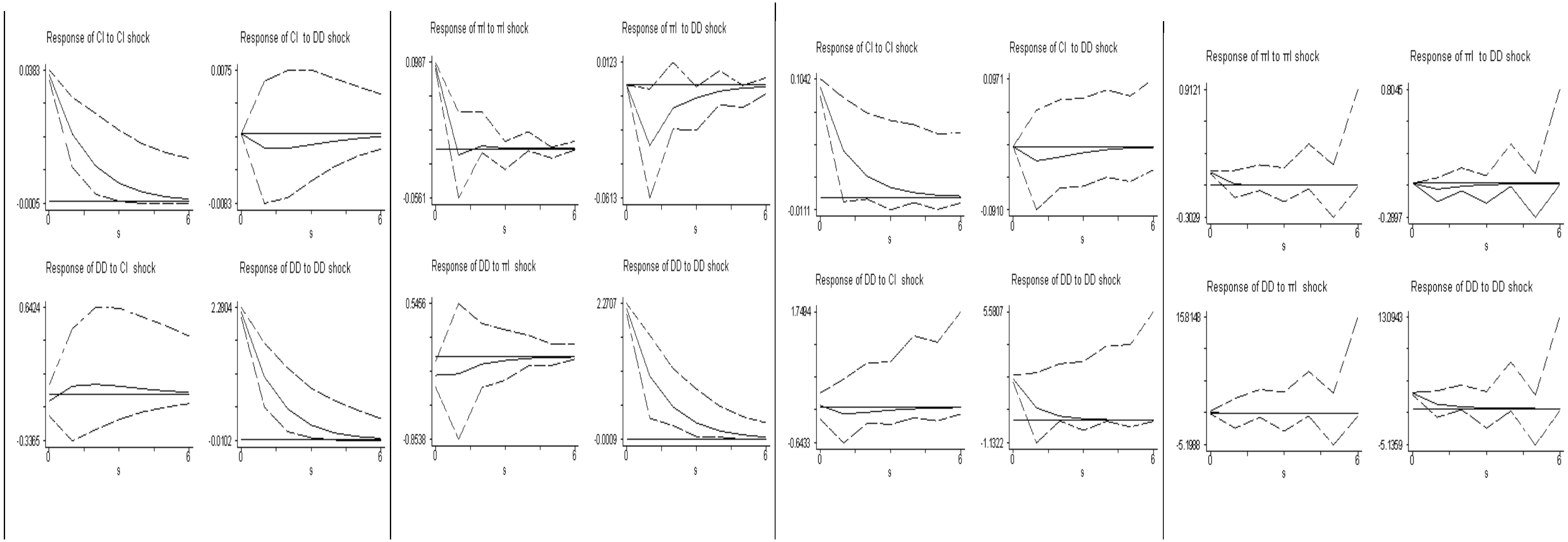


Dashed lines show 5% confidence interval using standard errors generated by Monte Carlo with 500 replications.

Figure 5: IRFs: CI, πI and DD.

Domestic **Foreign**

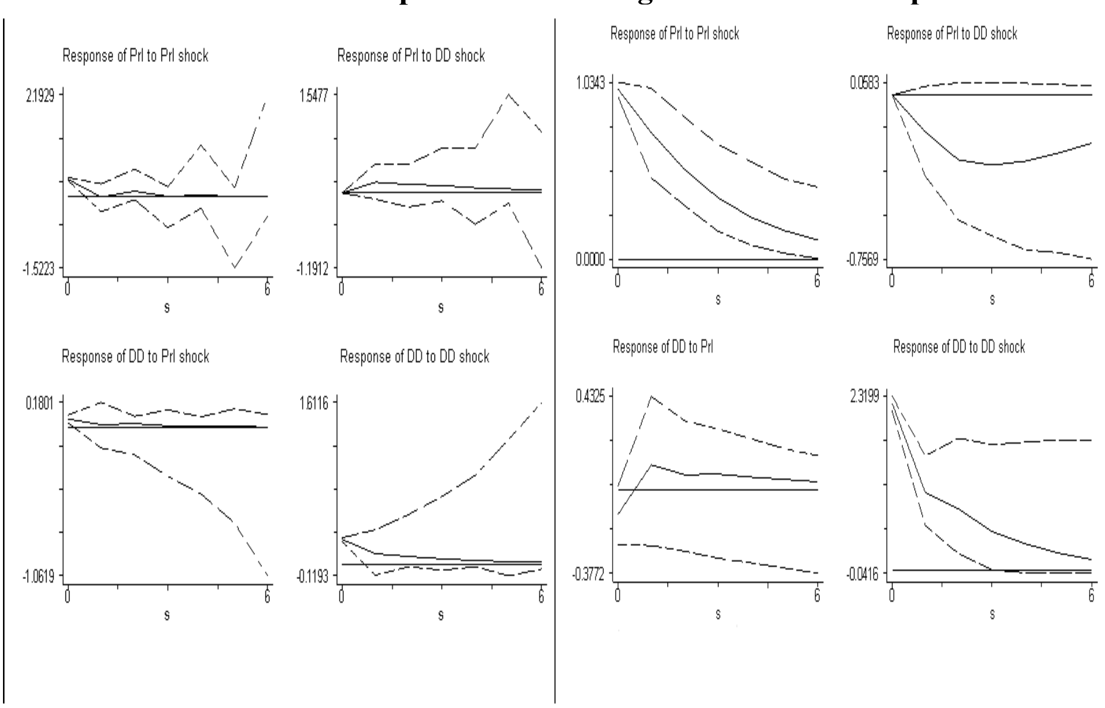
Cost **Profit** **Cost** **Profit**



Dashed lines show 5% confidence interval using standard errors generated by Monte Carlo with 500 replications.

Figure 6: IRFs: PrI and DD.

Low-Financial Developed **High-Financial Developed**

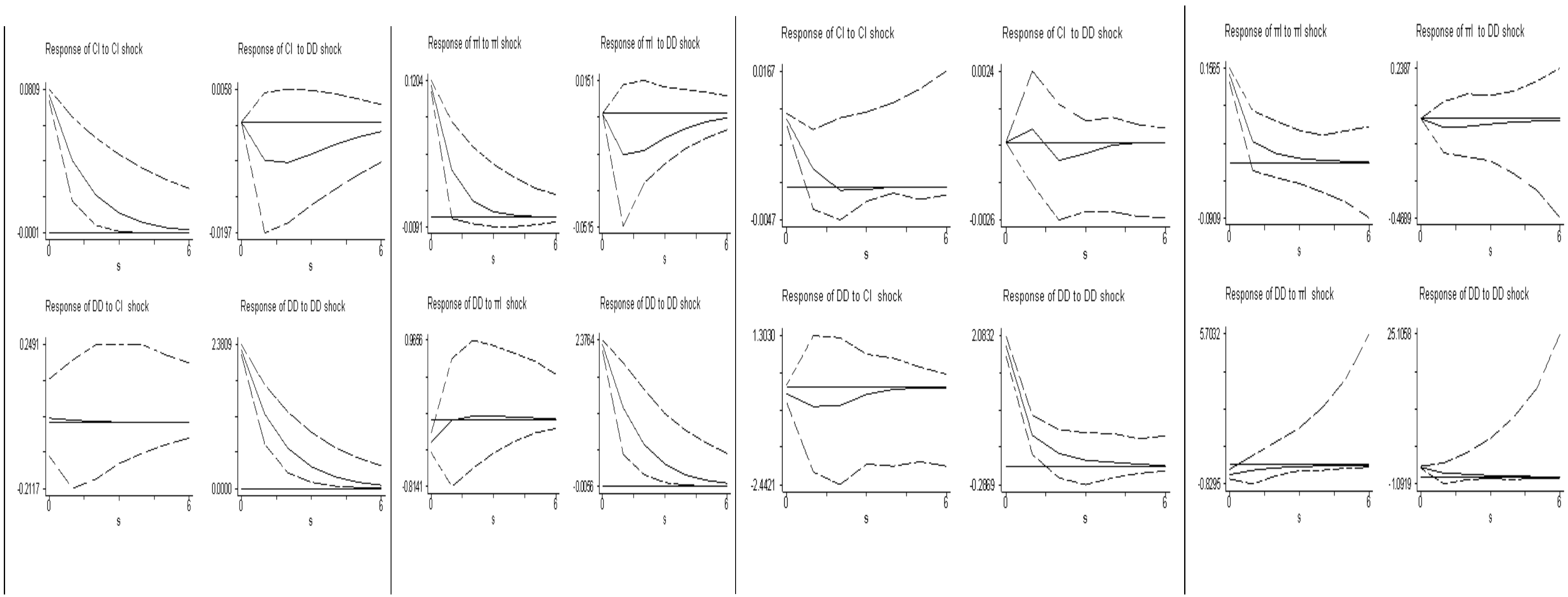


Dashed lines show 5% confidence interval using standard errors generated by Monte Carlo with 500 replications.

Figure 7: IRFs: CI, πI and DD.

High-Financial Developed Countries **Low-Financial Developed Countries**

Cost **Profit** **Cost** **Profit**



Dashed lines show 5% confidence interval using standard errors generated by Monte Carlo with 500 replication.

Appendix
Panel Var Specification

The value of the Panel-VAR analysis lies primarily on the error terms that are used to calculate impulse responses rather than on individual parameter estimates of the system of equations (Love and Zicchino, 2006). To this end, we solve the estimated model and obtain the moving average (MA) representation. This is done by recursive elimination of lagged independent covariates.[28]

The MA representation shows how the endogenous variables depend on the lagged residuals from the reduced form. The MA representation equates I_{it} and DD_{it} on present and past residuals e_1 and e_2 from the Panel-VAR estimation:

$$\begin{aligned} I_{it} &= a_{10} + \sum_{j=1}^{\infty} b_{11j} e_{1it-j} + \sum_{j=1}^{\infty} b_{12j} e_{2it-j} \\ DD_{it} &= a_{20} + \sum_{j=1}^{\infty} b_{21} j e_{1it-j} + \sum_{j=1}^{\infty} b_{22j} e_{2it-j} \end{aligned} \qquad \text{(A1)}$$

Under the endogeneity assumption the residuals will be correlated and therefore the coefficients of the MA representation are not interpretable. As a result, the residuals must be orthogonal. We orthogonalize the residuals by multiplying the MA representation with the Cholesky decomposition of the covariance matrix of the residuals. The orthogonalized, or structural, MA representation is:

$$\begin{aligned} I_{it} &= \alpha_{10} + \sum_{j=1}^{\infty} \beta_{11j} \varepsilon_{1it-j} + \sum_{j=1}^{\infty} \beta_{12j} \varepsilon_{2it-j} \\ DD_{it} &= \alpha_{20} + \sum_{j=1}^{\infty} \beta_{21j} \varepsilon_{1it-j} + \sum_{j=1}^{\infty} \beta_{22j} \varepsilon_{2it-j} \end{aligned}$$

and (A2)

[28] Note that this approach depends crucially on the assumption that the underlying data generating process of our variables is stationary (Maddala and Wu, 1999; Im et al., 2003). Preliminary results show that our variables are stationary. This is true given that the inefficiency scores are bounded time series. Nevertheless, unit roots tests were carried out for all inefficiency scores, providing evidence of strong stationarity (results are available under request). Unit roots tests for the distance to default are included in the appendix (see table A3).

$$\begin{pmatrix} \beta_{11j}\beta_{12j} \\ \beta_{21j}\beta_{22j} \end{pmatrix} = \begin{pmatrix} b_{11j}b_{12j} \\ b_{21j}b_{22j} \end{pmatrix} P \begin{pmatrix} \varepsilon_{1it} \\ \varepsilon_{2it} \end{pmatrix} = P^{-1} \begin{pmatrix} e_{1it} \\ e_{2it} \end{pmatrix}$$

where P is the Cholesky decomposition of the covariance matrix of the residuals:

$$\begin{pmatrix} Cov(e_{1it}, e_{1it})Cov(e_{1it}, e_{2it}) \\ Cov(e_{1it}, e_{2it})Cov(e_{2it}, e_{2it}) \end{pmatrix} = PP^{-1} \qquad \text{(A3)}$$

The orthogonal residuals can be interpreted as shocks: ε_{1it} is a shock in inefficiency and ε_{2it} is a shock in the distance to default. The coefficients in the equations (A2) give the current response of the left-hand side variable to shocks occurring j periods ago. The advantage of this reduced form Panel-VAR specification is that we can assess the dynamic interdependencies between inefficiency and risk with the minimum of restrictions imposed.

Table A1: Frontier estimates

	CI		*πI*		*PrI*		
	Coef.	*p-value*	*Coef.*	*p-value*		*Coef.*	*p-value*
lnp_1	0.101	0.000	0.706	0.000	**x_1**	0.548	0.000
lnp_2	0.899	0.000	0.294	0.000	**x_2**	-0.017	0.000
lny_1	-0.057	0.059	-0.141	0.121	**x_3**	0.479	0.000
lny_2	0.086	0.008	0.110	0.181	**x_4**	-0.067	0.000
lnn_1	0.161	0.000	-0.670	0.000	**y_1**	-0.002	0.000
lnn_2	0.129	0.000	-0.332	0.000	**y_2**	0.012	0.000
lnp_1^2	-0.087	0.000	-0.108	0.000	**x_1^2**	-0.031	0.000
lnp_2^2	-0.087	0.000	-0.108	0.000	**x_2^2**	0.000	0.372
lnp_1lnp_2	0.087	0.000	0.108	0.000	**x_3^2**	-0.015	0.000
lny_1^2	0.004	0.235	-0.010	0.504	**x_4^2**	-0.005	0.000
lny_2^2	0.046	0.000	0.068	0.002	**x_1x_2**	0.001	0.000
lny_1lny_2	-0.084	0.000	-0.102	0.000	**x_1x_3**	0.021	0.000
lnp_1lny_1	0.059	0.000	0.059	0.000	**x_1x_4**	0.009	0.000
lnp_2lny_1	-0.059	0.000	-0.059	0.000	**x_2x_3**	-0.002	0.000
lnp_1lny_2	0.045	0.000	0.031	0.001	**x_2x_4**	0.000	0.000
lnp_2lny_2	-0.045	0.000	-0.031	0.001	**x_3x_4**	-0.004	0.000
lnn_1^2	-0.082	0.000	0.020	0.602	**y_1^2**	0.000	0.000
lnn_2^2	0.048	0.000	-0.003	0.868	**y_2^2**	0.271	0.000
lnn_1lnn_2	-0.003	0.690	0.011	0.568	**y_1y_2**	0.000	0.000
lnn_1lny_1	0.055	0.000	0.033	0.003	**y_1x_1**	-0.001	0.000
lnn_1lny_2	0.016	0.103	-0.003	0.913	**y_1x_2**	0.000	0.000
lnn_2lny_1	-0.013	0.000	0.042	0.000	**y_1x_3**	0.001	0.000
lnn_2lny_2	-0.025	0.000	-0.033	0.035	**y_1x_4**	0.000	0.000
lnp_1lnn_1	-0.051	0.000	-0.072	0.000	**y_2x_1**	-0.002	0.000
lnp_2lnn_1	0.051	0.000	0.072	0.000	**y_2x_2**	0.000	0.000
lnp_1lnn_2	-0.027	0.000	-0.040	0.000	**y_2x_3**	0.002	0.000
lnp_2lnn_2	0.027	0.000	0.040	0.000	**y_2x_4**	0.000	0.000
T	-0.007	0.634	0.032	0.374	**t**	0.096	0.000
T^2	-0.003	0.145	-0.007	0.163	**t^2**	-0.018	0.000
$Tlnp_1$	-0.022	0.000	-0.012	0.001	**tx_1**	0.042	0.000
$Tlnp_2$	0.022	0.000	0.012	0.001	**tx_2**	0.000	0.000
$Tlny_1$	0.009	0.000	0.002	0.619	**tx_3**	-0.049	0.000
$Tlny_2$	0.004	0.104	0.016	0.009	**tx_4**	0.007	0.000
$Tlnn_1$	-0.011	0.001	-0.019	0.012	**ty_1**	0.000	0.000
$Tlnn_2$	-0.001	0.655	0.003	0.564	**ty_2**	0.000	0.000
lnTA	0.760	0.000	0.236	0.000	**constant**	0.333	0.000
lnInf	-0.001	0.587	-0.004	0.623			
lnGDP	0.092	0.014	-0.377	0.000			
lnHHI	-0.012	0.736	0.016	0.870			
lnCAP	-0.098	0.000	-0.020	0.765			
lnBRANCH	-0.067	0.029	0.107	0.247			
lnINTR	-0.024	0.533	0.132	0.220			
lnASFOB	0.015	0.220	-0.014	0.662			
lnNPL	-0.013	0.439	-0.069	0.170			
lnSPR	-0.027	0.151	-0.128	0.010			
lnLIQ	0.017	0.112	0.011	0.756			
Constant	-3.683	0.000	20.590	0.000			
λ (θ for πI)	8.503	0.000	3.308	0.000		2.144	0.000
σ_v	0.114	0.000	0.605	0.000		0.628	0.000
Log likelihood	859.737		-874.692			-2973.182	
σ_v^2	0.013		0.031			0.071	
σ_u^2	0.014		0.335			0.324	
Obs	1141		1141			1044	

Table A2: Choosing the optimal lag order for the panel VAR.

	Lag	AR(1)	AR(2)	AR(3)	AR(4)	Sargan	AIC	S-F W*
CI on CI and DD	1	-3.15***	-0.88			29.83	-4.88	0.91 [0.01]
	2	-1.46	1.22	-0.91		61.47**	-4.80	0.92 [0.02]
	3	-1.83*	1.63	0.04	1.17	70.3***	-4.78	0.92 [0.02]
πI on πI and DD	1	-2.21**	0.66			75.07	-4.88	0.90 [0.01]
	2	-1.17	0.77	-1.44		64.64**	-4.80	0.89 [0.01]
	3	-1.32	-0.25	-0.90	0.90	63.30**	-4.79	0.94 [0.01]
PrI on PrI and DD	1	-1.92*	0.42			36.62	-4.92	0.99 [0.03]
	2	0.955	-0.75	-0.31		66.22**	-4.82	0.99 [0.01]
	3	0.918	-0.78	1.05	0.18	53.88**	-4.81	0.98 [0.01]
DD on CI and DD	1	-3.74**	1.619			37.76	-1.70	0.94 [0.01]
	2	1.850	-0.19	0.50		67.3***	-1.69	0.99 [0.01]
	3	-0.48	-1.58	-1.62	1.66	67.4***	-1.64	0.99 [0.01]

Note: AR tests refer to Arrelano Bond serial correlation tests. DD is the distance to default, CI is the cost inefficiency, πI is the profit inefficiency, and the PriI is the productive inefficiency. Results do not alter for changing the ordering of variables in the reduced VAR. S-F W' stands for the Shapiro-Francia normality test.

Table A3: Panel Unit root test

	CI: lag 1		***πI: lag 1***	
Method	Statistic	Prob.**	Statistic	Prob.**
Levin, Lin & Chu t*	-40.2752	0.0000	-32.5910	0.0000
Breitung t-stat	-4.95548	0.0000	-6.04261	0.0000
Im, Pesaran and Shin W-stat	-11.9180	0.0000	-8.72232	0.0000
ADF - Fisher Chi-square	941.366	0.0000	799.617	0.0000
PP - Fisher Chi-square	893.343	0.0000	757.820	0.0000
Hadri Z-stat	16.8364	0.0000	13.7894	0.0000

	PrI: lag 1		***DD: lag 1***	
Method	Statistic	Prob.**	Statistic	Prob.**
Levin, Lin & Chu t*	-510.863	0.0000	-45.2724	0.0000
Breitung t-stat	-1.95686	0.0252	-5.04828	0.0000
Im, Pesaran and Shin W-stat	-40.4010	0.0000	-11.3502	0.0000
ADF - Fisher Chi-square	578.807	0.0000	692.508	0.0000
PP - Fisher Chi-square	580.018	0.0000	700.386	0.0000
Hadri Z-stat	15.8331	0.0000	13.6511	0.0000

Note: DD is the distance to default, CI is the cost inefficiency, πI is the profit inefficiency, and the PrI is the productive inefficiency. Probabilities for Fisher tests are computed using an asymptotic Chi-square distribution. All other tests assume asymptotic normality.