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RISK-RETURN EFFICIENCY AND RISK DETERMINANTS OF THE EUROPEAN BANKS

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Abstract

This study examines risk-return efficiency frontier and risk determinants for 36 banking systems of the European countries. The banks of European developed countries appeared more efficient than the banks of the transition and South East European (SEE) countries. In contrast to other studies, risk was measured as deviation from expected return that we derived through a utility maximization model. We found that volatility of return on assets (ROA) and return on equity (ROE) affects risk positively. In addition, we found that the banking systems of transition countries respond less to changes in volatility of ROA and ROE than the banking systems of European developed countries. Moreover, our robustness check model confirmed that the risk measure that was used can be explained by conventional risk proxies such us Z-score and equity ratio.

Keywords: *banking efficiency, risk, emerging markets, European countries*

JEL Classification: *G21, G14*

1. Introduction

In many emerging and developed markets, comparisons of banking sector efficiency and risk have been in the spotlight because of the occurrence of 2008 global financial crisis.The 2008 financial crisis profoundly reshaped the global banking landscape, emphasizing the critical relationship between risk appetite and efficiency within the banking industry. The crisis revealed that excessive risk-taking, often fueled by inadequate regulatory oversight and flawed incentive structures, created significant systemic vulnerabilities. Before the crisis, banks with higher risk appetites were regarded as top performers, but during the turmoil, they faced severe losses, exposing weaknesses in their operational models and triggering widespread industry reforms. This context highlights how misaligned risk strategies can result in inefficiencies and systemic failures.

Many researchers, practitioners and regulators try to assess and compare banking system efficiency and risk behavior, trying to identify the worst performing banks as they may jeopardize stability. Hence, the banking sector is considered as very important for economic development, because the link between economic growth and financial development has

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been well established (Dong and Men 2014; Levine 1997). The forces of deregulation, globalization and technological change have contributed to banking sector development (Fiordelisi, Marques-Ibanez, and Molyneux 2011). Therefore, the need to understand bank risk determinates and bank efficiency has been highlighted by the recent crisis (Festić, Kavkler, and Repina 2011).

In this study, we examine two issues that are important to the European banking sector. First, we extend the previous research on efficiency and risk by measuring the banking risk-return efficiency (RRE), where the risk preferences are derived from a utility maximization model as suggested by Hughes *et al*. (1996). Hence, failing to take into account risk might lead to misspecification of the efficiency model and to biased results (Hughes and Mester 2013). The banks that earn lower profits are not necessarily less efficient than banks with higher profits, if the former have traded-off a lower risk for lower profit. In view of that, we estimate the risk-return efficiency scores for banks and compare the banking systems of groups of transition, developed and South East European countries. In order to check whether estimations are consistent, we have included the profit efficiency model as a check on robustness.

Secondly, we recover the risk through the Generalized Managerial Utility function[1] from observed choices of production plans that banks have made, conditional on the expected return and its distribution. We abandon the assumption that managers are risk neutral. A unique aspect of our paper is identification of the determinants that affect risk preferences that managers assign to production plans subject to their conditional expected return distribution. Thus, we examine how the expected return distribution[2] (i.e. risk) is affected by the bank level and environment indicators. As the bank level indicators we include volatility of return on assets (vROA) and volatility of return on equity (vROE), because as the volatility of ROA and ROE increases, the banks may expect that the prices of deposits, bonds and subordinated debt will increase. Hence, the increase in distribution of expected return. We include the lag vROA and vROE as well, in order to check effects of previous periods on risk and to control for endogeneity. The leverage, debt to equity, we use as a proxy for capital structure, as suggested by Demirguc-Kunt and Huizinga (1999, 2000). Moreover, environment predictors that might affect risk preferences are GDP growth and credit growth as proxies for the demand side of the economy. Further, the Herfindahl index (HHI) presents the structure of the banking industry in terms of assets.

Our paper contributes to the literature in several ways. First, we extend the previous work of Hughes *et al.* (1996, 2000) by examining what affects the risk that managers assign to production plans. Secondly, unlike many banking efficiency studies that estimate efficiency using a standard approach (Fries and Taci 2005; Košak, Zajc, and Zoric 2009; Mamatzakis 2012), we estimate RRE efficiency by taking account of risk preferences. Our study comprises annual data for most European[3] countries (36 countries), with the time span 2007-2014. This comprehensive database allows us to compare different regions in Europe, e.g. transition countries with European developed countries; South East European (SEE) countries with other parts of Europe. Very few studies have used this methodology (Koetter, 2008; De Jonghe, Disli, and Schoors 2012; Hughes and Mester 2013); none to our knowledge covers European countries in one set. In addition to the Almost Ideal Demand System (AID) that we use to recover the risk variable and Stoachstic Frontier Approach (SFA) to measure the RRE efficiency score, we use a dynamic panel econometrics model to capture the effects of predictors on risk through the years; hence the simple panel model might suffer from correlation of the error term with lagged variables. As a robustness test, we use Z-score, a measure of risk that has been used widely in risk studies.

The paper is organized as follows:. Section 2 contains a literature review on banking efficiency and risk. Section 3 covers the methodology and data. The empirical results are interpreted in Section 4. In Section 5 a robust test is presented for the risk model. The last Section includes the conclusions.

2. Literature review

There is a set of literature that tries to examine banking efficiency and risk. One of the important studies of efficiency measurement was Leibenstein (1966). Since then many studies on banking efficiency have emerged (Altunbas, Evans, and Molyneux 2001; Aysan, Karakaya, and Uyanik 2011; Banerjee 2012; Bonin, Hasan, and Wachtel 2005; Fries and Taci 2005; Košak, Zajc, and Zoric 2009; Lensink, Meesters, and Naaborg 2008) for many countries. However, these studies do not take into account the risk preference of the banks. Even those that account for risk do it by including equity as suggested by Hughes and Mester (1993).

Recent studies have advanced the understanding of banking risk and efficiency measurement by employing innovative methodologies and exploring diverse determinants. Some of the studies that try to account for risk while measuring banking efficiency are Altunbas, Liu, Molyneux, and Seth (2000); DeYoung, Hughes, and Moon (2001); Fiordelisi, Marques-Ibanez, and Molyneux (2011); Hughes and Mester (2013; and Hughes (1999). These studies found that risk is an important ingredient for measuring efficiency. Hence, the banks may trade off profit and risk. Koetter (2008) showed that for German banks the ranking of banking efficiency changes when risk preferences change. Altunbas *et al.* (2000) showed that if the risk factors are not included the optimal banking size tends to be overstated. Moreover Shair *et al.* (2021) showed that the credit and liquidity risks have positive whereas insolvency risk has negative correlation with the efficiency. Khan, Kutan, and Qureshi (2024) included the fintech in efficiency measurment and their study shows interesting U-shaped relationship between fintech integration and bank efficiency, revealing initial inefficiencies before reaching a critical threshold where fintech adoption enhances performance. As Hughes *et al*. (2000) mentioned, there are two streams of studies: those that try to examine efficiency through microeconomics techniques but usually fail to take into account the risk preferences of banking managers; and those which explore incentives for risk taking, but ignore the microeconomics of bank production. For instance, Fiordelisi, Marques-Ibanez, and Molyneux (2011) relate banking efficiency to risk through the inter-temporal model and used non-performing loans (NPL) and expected default frequency as a proxy for risk. They measure the cost efficiency without taking into account risk preferences. Risk is a crucial calculation in banking but the delicacy of managing risk through the production function and risk incentives are two things that are very important in banking owing to social costs that banks incur (Honohan and Klingebiel, 2003; Dell'Ariccia, Detragiache, and Rajan 2008).

Several studies have tried to find what affects risk in the banking sector, by using as dependent variables NPL, Z-score and loan-loss provision. For example, Kasman and Kasman (2015) show that risk is affected by the competition; they use NPL as risk. However, using NPL as a proxy for risk might not reveal the best risk determinants because the NPL is an ex-post event (Fiordelisi, Marques-Ibanez, and Molyneux 2011). Fiordelisi, Marques-Ibanez, and Molyneux (2011) used NPL and as explanatory variables used capital and efficiency. Bhagat, Bolton, and Lu (2015) used Z-score as dependent, where they found that bank size is positively correlated with risk. They also found that risk is not linearly affected about the time of pre-crisis, during crises and after crises. Moreover, Gulati (2022) estimated risk-adjusted efficiency for banks of India by using internal risk factors of the bank, where they credit public banks as more efficient to persue regulatory objectives.

Hughes *et al*. (1996) and Hughes *et al*. (2000) developed a new measure of risk through the framework of the utility maximization problem by using AID. One of the first studies that used this measure of risk was Hughes *et al.* (1996); they regressed the volatility of deposit transaction on the risk. However, they used a static model that may have had an endogenity problem. Moreover, Hua and Liu (2010) also used risk as the left hand side variable, trying to find out if this new measure of risk is related to conventional risk proxy variables. They showed that the conventional risk proxy variables could not explain much the variance of the new risk. Thus, the new risk variable may contian much more information.

Overall, there is a lot of literature that measures banking efficiency and risk. However, to our knowledge, there are no studies that cover this large set of countries. We offer new evidence by examining banking efficiency in the risk-return aspect. Moreover, we offer a new insight into risk and its determinants.

3. Methodology and data

In this Section we will depict the methodology that enables us to measure efficiency while taking into account risk preferences. Moreover, we will try to identify the determinants that affect the risk preferences of banking managers. As a measure of risk we use standard deviation of the expected return, which we recover from a Generalized Managerial Utility function (Hughes *et al*., 1996). For the robust measure we use Z-score index, which is used in many studies as a risk measurement variable, e.g. Hesse and Cihak (2007); Fang, Hasan, and Marton (2011); Liu, Molyneux, and Nguyen (2012); and Hogan (2014).

3.1. Recovering risk from production technology

To capture the risk preferences of managers that they assign to the production function we will use the methodology that was first adopted by Hughes *et al.* (1996). The managers maximise utility by choosing optimal profit and input demand. Let π denote after tax profit. Technology stipulates the production plan of output quantities y, input quantities x, and capital k. The output prices are denoted by p. Managers form beliefs conditional on future states of the world s as interaction with the production plan (y,x,p,k) to determine profit π=($y,x,p,k/s$). Moreover, they form a subjective distribution of the prevailing states s. Therefore, this creates the conditional probability distribution of profit to be realised $f(\pi|y,x,p,k,s)$. Thus, the first and second moments of the conditional probability distribution of profit recover the expected profit and the risk $U[E(\pi),S(\pi)]$ (Hughes and Mester, 2013).[4]Since this risk modelling would not reveal the source of uncertainty which determines $S(\pi)$, Hughes *et al*. (2000) suggested that the production plan (y,x,p,k) can influence the utility of managers.

Generalized Managerial Utility function: managers maximize utility $U(\pi,y,x,p,k)$ subject to a transformation function of the form $T(y,x,k)$ and the rank preferences of profit. Let m denote noninterest income, $p{*}y$ denote interest income and $w{*}x$ denote the costs (w is a vector of input prices). In addition, let t be tax rate on profit so that p_π=1/(1-t) depicts the price of after tax profit in terms of before tax profit. Then, the nominal before tax accounting profit is given as (Hughes *et al*., 1996):

$$p_\pi\pi=py+m-wx \tag{1}$$

under the assumption of perfect competition in input and output markets. This ensures comparability with the case of the cost efficiency. Therefore, we write the Utility maximization problem:

$$\begin{aligned}&\max_{\pi,x} U(\pi,y,x,p,k)\\ &s.t.\quad p_\pi\pi+wx=py+m,\\ &s.t.\quad T(y,x,k)\le 0\end{aligned} \tag{2}$$

Solving this maximization problem for π and x_i, we get the most preferred profit function and the most preferred input demand function:

$$\pi^*=\pi^*(y,v,m,k) \tag{3}$$
$$x_i^*=x_i^*(y,v,m,k) \tag{4}$$

where v is a vector of the price environment of the bank $v=(w,p,p_\pi)$. The profit function π^* depicts preferences of managers by taking into account the trade-offs of their objectives. Risk preferences are recovered from observed choices of production plans that banks have made. While the most preferred profit demand function is conditional on risk preferences we use it to estimate the benchmark frontier and to derive efficiency estimates. Moreover, we use recovered risk preferences as a response variable to a set of explanatory variables.

3.2. Empirical specification: Risk-Return efficiency

In order to recover risk in the empirical approach, Hughes *et al*. (1996) used the Almost Ideal Demand System (AID) that was developed by (Deaton and Muellbauer 1980). The AID enables us to derive the most demand function for profits and inputs through Shephard's lemma managerial expenditure function, where the duality of the maximization problem from eq. (2) exists. In the following, we will briefly reintroduce the empirical model but for more details see (Hughes *et al*., 1996; 2000) and appendix 3. The AID allows us to derive the demand function of profits and inputs in terms of expenditure shares; in the banking case, total revenue $p*y+m$:

$$\begin{aligned}&\frac{\partial\ln E}{\partial\ln p_\pi}=\frac{p_\pi\pi}{py+m}=\frac{\partial\ln P}{\partial\ln p_\pi}\\ &\quad+\mu[\ln(py+m)-\ln P]\end{aligned} \tag{5}$$

and

$$\begin{aligned}&\frac{\partial\ln E}{\partial\ln w_i}=\frac{w_ix_i}{py+m}=\frac{\partial\ln P}{\partial\ln w_i}\\ &\quad+v_i[\ln(py+m)-\ln P]\end{aligned} \tag{6}$$

where $lnP=\alpha_0+\sum_i \alpha_i lnz_i$ + (1/2) $\sum_i\sum_j \alpha_{ij}\ lnz_i\ lnz_j$; is a price index in AID and $z=(y, v)$ and $v=(w, \tilde{p},p_\pi)$.

Note that $\tilde{p}$ is the average price of outputs (see Table 1), because it is difficult to get data for the price of each output and we preserve more degrees of freedom (Hughes *et al*., 1996). In contrast to Hughes *et al*. (1996) and Hughes *et al*. (2000) that treat equity as endogenous, we follow Koetter (2008) and include equity only in share equations.

We use nonlinear seemingly unrelated regression[5] (nlSURE) for derivation of input and profit functions. We follow the method of Hughes *et al*. (1996)[6] and use eq. 5 to measure expected profit. Expected return on equity, $ER=\frac{E(p_\pi\pi)}{k}$, is expected profit divided by financial capital, whereas, risk R is measured as a standard error of the expected return, $R=S(\frac{E(p_\pi\pi)}{k})$. Then we follow with efficiency measures[7] by taking into account risk

$$\begin{aligned}&\boldsymbol{Z}_{it}=\alpha_i+\beta_1R_{it}+\beta_2R_{it}^2\\ &+\delta_i\boldsymbol{h}_{it}+\varepsilon_{it}\end{aligned} \tag{7}$$

where **Z**=(ER, Profit) for bank i at time t, h is a vector of control variables and ε_{it} is composed of random noise and inefficiency. Including macroeconomic variables is essential to account for country characteristics that could effect the results. For control we include structure and environment variables[8]: concentration[9] controls for structural banking sector effects; Loan to Deposits control for funding restrains GDP growth reflect economic environment; credit growth controls for financial activities; Market share for deposits control for concentration; and Asset size control for difference in size of the industry. These control variables help isolate the true impact of risk by accounting for broader economic, financial, and structural factors that influence bank efficiency. Their inclusion ensures a more robust and accurate analysis.

All variables are transformed into natural logarithm except risk and asset size which are divided in three categories: small, medium and large (for details see Section 3.4 Data and Variables), because of heterogenity. We have two models, one being the expected return efficiency and second the profit efficiency. For each model we use two specifications, by including and omitting asset size, and by including the market share of deposits.

3.3. Empirical specification of Risk

In order to examine the hypothesis of how volatility of return on assets affects risk preferences, we use the following regression:

$$Risk_{it} = \alpha + \gamma_1 Risk_{i,t-1} + \beta_1 vROA_{it} + \beta_2 vROA_{t-1} + \theta_i \boldsymbol{X} + \varepsilon_{it} \tag{8}$$

$$Risk_{it} = \alpha + \delta_1 Risk_{i,t-1} + \delta_1 vROE_{it} + \delta_2 vROE_{t-1} + \varphi_i \boldsymbol{X} + \varepsilon_{it} \tag{9}$$

where Risk_{it} is the deviation of expected return for bank i at time t. We used the lag risk following the studies of Salas and Saurina (2002), Fiordelisi, Marques-Ibanez, and Molyneux (2011), and Jiménez, Lopez, and Saurina (2013) to measure persistency of risk. The vROA and vROE are expected to have a positive effect on Risk; hence the study of Merton (1974) showed that volatility of assets is related to the value of the firm through risk perception. Thus, we test if the volatility of ROA and ROE affects the risk; hence managers perceive risk as deviation from the expected returns. **X** is a vector of control variables that we assume might affect risk. We include GDP growth as a measure of economic development; HHI as industry concentration; loan to deposit ratio as a measure of intermediation; loan growth of the banking industry; and debt to equity as leverage. We use GMM in order to avoid serial correlation problems and to account for dynamics (Arellano and Bond 1991; Blundell and Bond 1998). We estimate eqs. (8) and (9) using four specifications. In specification [1], we only regress the risk on lag risk and volatility of assets. In specification [2], we include the control variables but we do not control for region. In specification [3], we extend the calculation by including dummy variables for transition countries (1, otherwise zero), and interaction between volatility of ROA and transition countries.

We have made the model dynamic by including the lag of the dependent variable. In addition, we have included the volatility of ROA and ROE, and their lags, because the volatility in a previous period might affect the distribution of the expected return at the current time. Hence, the banks anticipate that higher volatility might not have the predicted effect on their expected return. Moreover, in our study we examine how risk in the banking systems of South East European, Transition and European developed countries responds to the volatility of ROA and ROE. We hypothesize that South East European and Transition countries as a group respond less to volatility of ROA and ROE because of their less developed markets. The banks in the European developed countries are integrated in the financial market and capital market; thus, the change in volatility of ROA and ROE has more impact than in the other group of countries because of the market discipline.

We expect that there should be a difference in risk between the banking systems in transition countries and those in developed countries, because the banking systems in the European developed countries are more prone to react when there is volatility of ROA due to the market discipline effect (Casteuble, Nys, and Rous 2018). In specification [4], we include a dummy variable for South East European countries (1, otherwise zero) and interaction with volatility of ROA, in order to examine whether this region has a different attitude in relation to risk.

3.4. Data and variables

Our study uses a data set for 576 commercial banks from 36 countries of Europe; this consists of annual data for the years 2007 - 2014. The data set for banks is obtained from Bankscope. We adjusted the data for inflation and converted all the currencies to the Euro through the Bankscope platform. Macroeconomic data are obtained from World Bank Data. We have excluded banks that are not active. The Intermediation approach was used as suggested by (Sealey and Lindley 1977), where as output we use: gross loans (Y_1), other earning assets (Y_2) and securities (Y_3), all being measured in volumes of Euros. As inputs we use: cost of labor (W_1= personal expenses to total assets), cost of funds (W_2= interest expenses to interest bearing liabilities) and cost of fixed assets (W_3= non-interest expenses to fixed assets), the total cost (TC= interest expenses + personnel expenses + other operating expenses).

The descriptive statistics of the AID model for the variables are in Table 1; the lower panel describes the additional variables that are used in AID specification for recovering the expected return and risk (DeYoung, Hughes, and Moon 2001; Hughes *et al*., 2000; Hughes and Mester, 2013).

In Table 2 we depict the descriptive statistics of the variables that we use in eqs. 7, 8 and 9. The volatility of ROA was measured according to (Shehzad, Scholtens, and De Haan 2009) where the standard deviation of return on assets for bank *i* is estimated by using ROA of the current year and the two previous years. We have estimated the volatility of ROE in a similar manner.

The Market share in terms of deposit is estimated as (deposit of $Bank_{it}/\sum_{i=1}^{n} deposits\ Bank_{it}$ where n is the number of banks within the country and t is a year t=2007,…,2014); concentration is measured through the Herfindahl–Hirschman Index in terms of assets ($HHI = \sum_{i=1}^{n} Market\ share\ of\ assets_{it}^2$ where n is the number of banks within the national markets in the sample at time t=2007,..,2014). As an intermediate function variable we used loan to deposit in bank level. We used GDP growth and Asset to GDP as macroeconomic variables. In addition, we includ the credit growth of the banking industry ($Credit\ growth = ln(credit_t) - ln(credit(t\text{-}1))$).

Table 1. Descriptive statistics for variables used in AID to recover the expected profit and risk

Variable	Description	Mean	Sd	Min	Max
Y_1	Gross loans[1]	29,800	96,100	68	909,000
Y_2	Other earning assets[1]	31,400	141,000	75	830,000
Y_3	Securities[1]	13,300	56,600	0.54	880,000
W_1	Cost of labor[2]	0.05	0.03	0.01	0.17
W_2	Cost of funds[2]	0.04	0.05	0.01	0.32
W_3	Cost of fixed assets[2]	0.10	0.45	0.04	0.62
k	Equity[1]	2,929	9,823	0.988	95,000
TC	Total costs[1]	2,243	8,043	901	117,000
Pbt	Profit before tax[1]	118	1,491	-230	13,700
Tax	Tax rate[2, 3]	0.43	0.14	0.07	0.75
$\tilde{p}$	Mean output interest[2]	0.08	0.42	0.02	0.64
p_π	Price of after tax profit	1.91	0.64	1.08	4.07
SW_{w1}	Input labor share to revenue[2]	0.21	0.29	0.01	0.41
SW_{w2}	Input fund share to revenue[2]	0.39	0.23	0.09	0.43
SW_{w3}	Input FA share to revenue[2]	0.36	0.65	0.10	0.75
$SW_{p\pi}\ \pi$	Input profit share to revenue[2]	0.04	0.45	0.00	0.76
$py{+}m$	Revenue[1]	2,647	9,269	27	115,000

Notes: [1]in millions; [2] as a fraction; [3]tax rate measures the amount of taxes and mandatory contributions payable by businesses after accounting for allowable deductions and exemptions as a share of commercial profits. Source: Bankscope, World Bank, authors' calculation.

Table 2. Descriptive statistic of other variables used in models

Variable	Mean	Sd	Min	Max
Risk[1]	0.017	0.020	0.000	0.270
Volatility of ROA[1]	0.010	0.025	0.000	0.804
Volatility of ROE[1]	0.179	1.208	0.000	7.353
Market share of deposits[1]	0.071	0.126	0.000	0.984
HHI index[1]	2371	1294	1341	9844
Loan to Deposits[2]	1.430	1.522	0.000	2.810
GDP growth[3]	0.025	0.041	-0.132	0.172
Credit growth[1]	0.032	0.115	-0.512	0.527
Debt to Equity[2]	14.656	46.293	-5.250	51.000
Assets to GDP[3]	1.363	1.259	0.000	5.355

Source: [1]authors' calculations; [2]Bankscope; [3]World Bank Data

4. Results

Table 3 shows the results for the model risk-return frontier and profit efficiency as presented in eq. (7). The risk variable is positively related to the expected return, which is in line with our expectation. The parameters of risk, which we measured as deviation from expected return, in four specifications are also in line with findings of DeYoung, Hughes, and Moon (2001), Hughes *et al*. (1996), and Koetter (2008). Results suggest that the relationship between risk and expected return is nonlinear. If we take the partial derivative of eq. (7) $\frac{\partial ER}{\partial R} = 0$ and $\frac{\partial Profit}{\partial R} = 0$, we can find the maximum point of expected return and profit with respect to risk. In the first specification of the risk-return efficiency model, we find that, at the point where the standard deviation is 0.230, the expected return reaches a maximum; after this point the expected return falls (see appendix 1 for other specifications). This implies that banking managers trim down their expected return after the subjective distribution of the expected return increases beyond a certain point.

Market share of deposits is positive and significant in both models, implying that, as market share of deposits increases, other things being equal, the expected return increases. We find that GDP growth is positively related to the expected return, implying that managers expect higher returns when we have positive economic development. Moreover, in these specifications we have included the categorical variables for assets, where the benchmarks are the banks with assets from 0 to 250 mil. €. We found that expected return is affected by the large banks with assets above 500 mil. €. It might imply that managers perceive that an increase in banking size above a certain level will pay off through economies of scale. According to (Hughes and Mester 2013) economy of scale is evident in the banking industry in the USA. Furthermore, we found that credit growth affects the expected return positively, implying that, as credit growth of the banking industry increases, other things remaining constant, the expected return increases.

At the foot of Table 3, we provide the efficiency scores for each model for each group of countries. The banking industry in the European developed economies appears to be the most efficient, on average, in all models. The banking industry of the transition countries group has a higher efficiency score than that of the South East European countries, although there is not a significant statistical difference between the two groups.

Following (Kumbhakar and Lovell 2000), the specification of a stochastic frontier against the average response function, we find that parameter y (see Table 3) that is measured as the ratio of variation due to inefficiency relative to random noise is different from zero at the significant conventional level. This implies that the stochastic risk-return frontier is capturing efficiency.

Table 3. Risk-Return frontier and Profit frontier

	Risk-return efficiency frontier		Profit efficiency frontier	
	[1]	[2]	[1]	[2]
Risk	1.013***	0.787***	24.058***	27.648***
	(0.232)	(0.188)	(5.316)	(3.265)
$Risk^2$	-2.170**	-1.592*	-54.357*	-104.173***
	(0.701)	(.846)	(31.076)	(21.760)
HHI of assets	-0.032***	-0.041***	-0.346*	-0.908***
	(0.006)	(0.006)	(0.153)	(0.107)
loan to deposit	0.003	0.008***	0.103	0.558***
	(0.002)	(0.002)	(0.057)	(0.033)
Assets to GDP	-0.014***	-0.012***	0.056	0.322***
	(0.003)	(0.002)	(0.068)	(0.048)
GDP growth	0.021**	0.019**	0.009***	0.014**
	(0.010)	(0.009)	(0.001)	(0.012)
Credit growth	0.010***	0.014**	0.086*	0.011*
	(0.002)	(0.007)	(0.050)	(0.006)
ln market share of deposits		0.011***		0.697***
		(0.001)		(0.017)
Assets size (250/500 mil €)		-0.044		-1.658
		(0.056)		(1.602)
Asset size (>500 mil €)		0.225***		-0.593
		(0.051)		(1.310)
Constant	0.914***	0.635***	8.788***	10.325***
	(0.016)	(0.059)	(0.482)	(1.334)
$\sigma_s = \sigma_u + \sigma_v$	3.22***	4.15***	4.01***	3.79***
	(0.554)	(1.025)	(1.257)	(1.124)
$\gamma = \frac{\sigma_u}{\sigma_s}$	0.651***	0.623***	0.683***	0.672***
	(0.225)	(0.230)	(0.198)	(0.215)
Efficiency scores by:				
All countries	0.881	0.882	0.774	0.759
	(0.051)	(0.039)	(0.122)	(0.121)
European developed countries	0.922	0.915	0.812	0.811
	(0.031)	(0.041)	(0.213)	(0.104)
Transition countries	0.891	0.881	0.771	0.743
	(0.033)	(0.032)	(0.135)	(0.117)
South east European	0.831	0.851	0.738	0.722
	(0.021)	(0.020)	(0.161)	(0.122)

Notes: List of the countries in the sample is provided in Appendix 2; TC = Transition countries; SEE = South-east European countries. Standard errors are given in parentheses and *** denotes statistical significance at the 1% level, ** at the 5% level and * at the 10% level.

Results based on eqs. (8) and (9) are presented in Table 4. We found that Risk is persistent through the lag Risk at the significant level. These results are in line with those of (Fiordelisi, Marques-Ibanez, and Molyneux 2011) who examined EU commercial banks. The volatility of ROA and lag vROA appeared positively related to Risk in all specifications, at a statistically significant level. We found that volatility of ROA increases the risk, or, in other words, the higher the volatility of ROA, the higher the standard deviation of the expected return. This implies that managers perceive that the volatility of ROA affects the risk positively, which is in line with our expectation. The volatility of ROE and its lag affects the risk in the same way as vROA suggesting that results are in line with our expectations. But vROE and its lag are not statistically significant in all specifications.

In our case, GDP growth is negatively related to risk, implying that economic development affects risk negatively because managers expect that, as economic development increases, risk decreases. Credit growth also appears to affect risk negatively, implying that better prospects of credit growth decrease the standard deviation of the expected return, i.e. risk. Furthemore, the debt to equity ratio shows that, as leverage increases, holding other things constant, risk increases. This is in line with the financial literature. The size of the firm that we have measured as the normal logarithm of total assets, due to skewness, appeared positive and statistically significant.

In specifications [3], [4], [7] and [8] from Table 4 we show how the banking systems of the groups of countries perceive risk and how they react if there is a high volatility of ROA and ROE. In specifications [3] and [7] we have included dummy variables for transition countries, where the benchmark is the banking systems of the European developed countries. In specifications [4] and [8] we have included dummy variables for SEE countries, where the benchmark is all other countries in the sample. In specification [3] we included interaction between the banking systems of transition countries and volatility of ROA, and we find that banks in the transition countries are less sensitive to increases in volatility of ROA than those in the European developed countries. This implies that the banking systems of transition countries react much less to volatility of ROA than their counterparts in European developed countries. The mechanism behind this result might be that managers of banks in the European developed countries know that changes in the volatility of ROA will reflect in depositors, bondholders and subordinated debt holders (Casteuble, Nys, and Rous, 2018; Fernández, González, and Suárez, 2016). Thus, managers will increase the distribution of their expected return. In specification [4], the banking systems of SEE countries also appeared less sensitive to volatility of ROA than those of all other banking systems in the sample.

In the specifications where the volatility of ROE is included, we found similar results. In specification [7] we have included an interaction term between the banking systems of transition countries and volatility of ROE. The results show that banks in transition countries are less sensitive to changes in volatility of ROE than banks in European developed countries. Moreover, in specification [8] we found that banks in the SEE respond less to changes in volatility of ROE than all other banking systems in the sample. The similarity in results regarding the volatility of ROA and ROE might be due to the same mechanism: market discipline.

The parameters of IV are consistent, hence, the Sargan-Hansen test shows that the instruments are uncorrelated with the error term. The serial correlation of first order, AR(1), appeared significant, whereas the serial correlation of second order, AR (2), is not significant.

Table 4. Risk predictor variables

Dependent variables: Risk	Model [specifications]							
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
$Risk_{t-1}$	0.449***	0.414***	0.404***	0.409***	0.426***	0.399***	0.377***	0.376***
	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)
volatility of ROA	0.207***	0.231***	0.320***	0.293***				
	(0.031)	(0.031)	(0.040)	(0.036)				
volatility of ROA_{t-1}	0.097**	0.082**	0.052*	0.057*				
	(0.040)	(0.041)	(0.030)	(0.032)				
volatility of ROE					0.030	0.042*	0.024***	0.012***
					(0.023)	(0.024)	(0.005)	(0.002)
volatility of ROE_{t-1}					0.021	0.031	0.017**	0.009**
					(0.018)	(0.023)	(0.008)	(0.004)
Loan to deposit		0.020	0.010*	0.012*		0.022	0.030*	0.010
		(0.018)	(0.006)	(0.007)		(0.019)	(0.017)	(0.009)
GDP growth		-0.021**	-0.017*	-0.011*		-0.016	-0.016*	-0.018*
		(0.010)	(0.010)	(0.006)		(0.015)	(0.009)	(0.010)
Credit grwoth		-0.009*	-0.011*	-0.010**		-0.006**	-0.007	-0.008***
		(0.005)	(0.006)	(0.005)		(0.003)	(0.005)	(0.002)
Debt to Equity		0.010**	0.009**	0.004**		0.000**	0.022	0.019
		(0.005)	(0.002)	(0.001)		(0.000)	(0.019)	(0.020)
ln assets		0.002***	0.001	0.001**		0.001***	0.000	0.001**
		(0.000)	(0.001)	(0.000)		(0.000)	(0.001)	(0.000)
TC#			-0.004				-0.005*	
			(0.003)				(0.003)	
TC * volatility of ROA			-0.210***					
			(0.060)					
SEE				-0.001				-0.001
				(0.002)				(0.002)
SEE * volatility of ROA				-0.199**				
				(0.062)				
TC * volatility of ROE							-0.024***	
							(0.005)	
SEE * volatility of ROE								-0.012***
								(0.002)
Constant	0.008***	-0.025***	-0.002	-0.019**	0.009***	-0.017**	0.009	-0.017*
	(0.001)	(0.007)	(0.013)	(0.009)	(0.001)	(0.007)	(0.014)	(0.009)
AR 1 (p-value)	(0.011)	(0.031)	(0.034)	(0.021)	(0.032)	(0.043)	(0.035)	(0.031)
AR 2 (p-value)	(0.471)	(0.591)	(0.438)	(0.522)	(0.381)	(0.502)	(0.398)	(0.512)
Sargan-Hansen (p-Value)	(0.931)	(0.821)	(0.834)	(0.812)	(0.822)	(0.791)	(0.865)	(0.831)

Note: List of the countries in the sample is provided in Appendix 2; TC = Transition countries; SEE = South-east European countries. Standard errors are given in parentheses and *** denotes statistical significance at the 1% level, ** at the 5% level and * at the 10% level.

5. Robustness check

In this Section, we carry out a robust check of the risk model. In our robust model of risk, we use the Z-score according to the studies of Liu, Molyneux, and Nguyen (2012) and Hogan (2014). We regress the Z-score and the equity ratio on our risk variable. The Z-score and equity ratio are considered traditional risk variables. Thus, we want to show how much these well used variables explain the risk variable that we have used in this study.

The robustness check model is as follows:

$$Risk_{it} = \alpha + \beta_1 Zscore_{it} + \beta_2 Equity\ ratio_{it} + \varepsilon_{it} \quad (10)$$

The Z-score is measured as the sum of ROA and Equity ratio divided by the standard deviation of ROA. We have transformed the Z-score variable to natural logarithm Z-score due to normality. The Z-score shows how many standard deviations a return has to decline in order to drain equity, implying that the higher the Z-score the better the financial stability of the bank. Thus we expect a negative relationship with our risk variable.

The Equity ratio is measured as the ratio of equity to total assets. Equity ratio measures capitalization; this indicator shows the ability of the bank to absorb losses (Koetter, 2008). Thus, we expect that the higher the ratio, the lower the risk to the bank.

Table 5. Robustness model check estimation and descriptive statistics

	Estimated results	Descriptive statistics	
		Mean	SD$
Ln Z-score	-0.051** (0.021)	41.22	28.88
Equity ratio	-0.082*** (0.027)	0.11	0.052
Constant	0.014*** (0.001)		
Log likelihood	5504.110		
N	1850		

Standard errors are given in parentheses and *** denotes statistical significance at the 1% level, ** at the 5% level and * at the 10% level. R^2= 48.23%; $ Standard deviation.

We found that the Z-score is significant and negatively related to our risk variable. This result is in line with our expectation. Moreover, the equity ratio is also in line with our expectation and Koetter (2008), significant and negatively related to the risk variable.

The R2 = 48% shows how much these proxy variables of risk explain the variance of the risk variable that we have derived from the utility maximization model. Conclusively, we can say that these two variables does not exhaust all the domain, but we may conclude that the risk variable that we have derived from the utility maximization model is appropriate to capture effects of risk determinants.

6. Conclusion

In this study, we have investigated the banking systems of 36 European countries for the years 2007–2014, examining risk-return efficiency and risk determinants. We have used the utility maximization model to derive the risk measure, hypothesizing that volatility in ROA and ROE affects the standard deviation of the expected return, which we define as risk. Our results confirm that the volatility of ROA and ROE positively affects risk. This finding suggests that bank efficiency assessments should incorporate risk-appetatie rather than assuming that all banks operate with the same risk appetite. Otherwise, banks that take on higher risk may be mistakenly considered more efficient than their more risk-averse counterparts.

In addition, we found that the banking firms in the European developed countries react faster to changes in volatility of ROA and ROE than their counterparts in transition countries. The reaction might be due to higher exposure of the banking systems in European developed countries to market discipline (Casteuble, Nys, and Rous 2018).

The banking systems of Central and Eastern European (CEE) countries operate in less efficient markets (Guidi, Gupta, and Maheshwari 2011), potentially leading to mispricing of risk. These results highlight the need for stronger regulatory frameworks in transition economies to ensure that risk is accurately reflected in bank pricing and decision-making.

Moreover, we found that GDP growth and credit growth affect risk negatively, showing that managers decrease the deviation of the expected return as the prospect of the economy and industry improves. This supports the use of countercyclical macroprudential policies to prevent excessive risk-taking during periods of rapid credit expansion. Regulators should ensure that banking stability is maintained by monitoring lending growth and implementing appropriate capital buffers in times of economic expansion.The results of the model on risk-return efficiency reveal, as expected, that risk is positively related to expected return but in a nonlinear manner. The same results appeared in the profit efficiency model that we have included as a model comparison. We showed at what point the managers maximize the expected return with respect to risk, which has important implications for strategic decision-making in banks. We found that market share of deposits is positively related to the expected return and to profit, underscoring the importance of stable funding sources in improving bank efficiency.

The results for GDP growth and credit growth are positively related to the expected return, showing that expected return of banking managers increases as GDP and credit grow. Further, we found that expected returns are higher for banks with assets above 500 million Euro compared to banks with assets below 250 million Euro. This suggests that economies of scale contribute to better risk-adjusted returns, reinforcing the need for policies that support growth and financial stability among smaller banks. In the comparison of risk-return efficiency scores, we show that banking systems in the European developed countries have higher efficiency scores than banking systems in the transition and SEE countries. However, there is no significant difference in efficiency scores between banking systems in transition countries and SEE countries.

Finally, in the robustness check model we show that our proxy for bank risk is related to the Z-score and the equity ratio. This implies that our prediction of risk derived from utility maximization is related to traditional risk variables. The direction of effects of the coefficients are in line with our expectation. Thus, we may conclude that risk as measured in our study is appropriate and contains important information for policy makers, professionals and regulators.

Policy Recommendations

1. Incorporate risk-based assessments to ensure that banking efficiency comparisons account for differences in risk-taking behavior.
2. Implement countercyclical macroprudential policies to curb excessive risk-taking during credit booms and ensure financial stability.
3. Encourage risk-adjusted performance metrics to prevent the misclassification of high-risk banks as more efficient.
4. Support growth strategies for smaller banks to improve risk-return efficiency and competitiveness while maintaining financial stability.

Endnotes

1 Empirically we use the almost ideal demand system (AID) that was developed by Deaton and Muellbauer (1980).

2 By distribution we mean standard deviation of expected return.

3 We included most European continent countries (EU and non-EU members)

4 For more detail on this model see Hughes *et al*. (2000)

5 nlsure code in STATA, specifically for AID estimation.

6 We apply restrictions and symmetry requirements as suggested by Hughes and Mester (2013) appendix provided at the link www.philadelphiafed.org/research-and-data/publications/working-papers/2013/wp13-13R.pdf

7 We use log-likelihood function to estimate RRE frontier, a technique suggested by Olson, Schmidt, and Waldman (1980)

8 More detail for rational inclusion of macroeconomic variables see Chen and Lu (2021); Alfadli and Rojub (2019)

9 Concentration we measured as Herfindahl Index .

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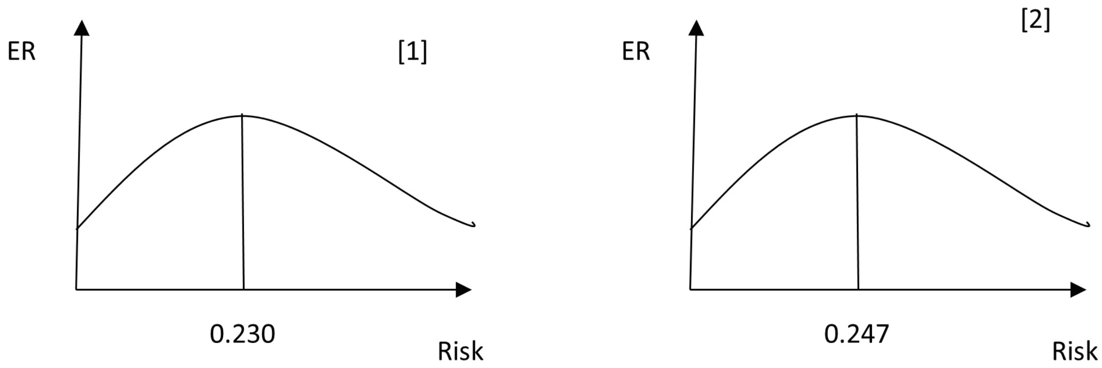
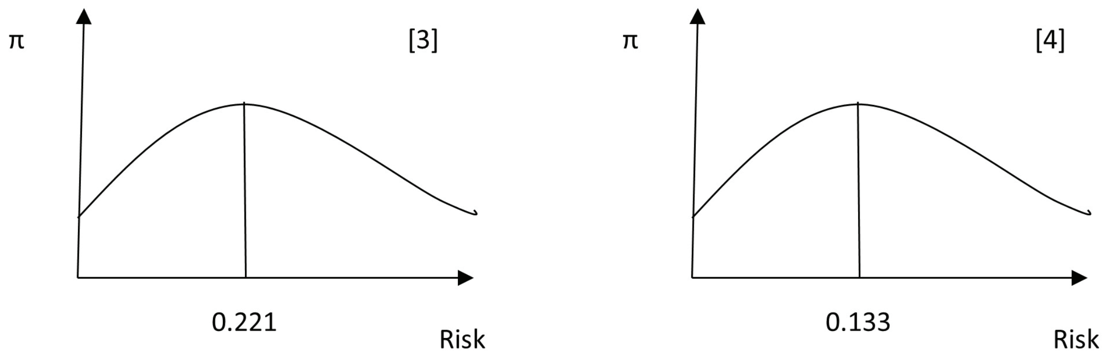
Appendix 1

Risk-Return efficiency frontier



Profit efficiency frontier



Appendix 2

	Country	European developed countries	Transtion countries	South East European countries
1	ALBANIA	0	1	1
2	AUSTRIA	1	0	0
3	BELGIUM	1	0	0
4	BOSNIA AND HERZEGOVINA	0	1	1
5	BULGARIA	0	1	1
6	CROATIA	0	1	1
7	CYPRUS	1	0	0
8	CZECH REPUBLIC	0	1	0
9	DENMARK	1	0	0
10	FINLAND	1	0	0
11	FRANCE	1	0	0
12	GERMANY	1	0	0
13	GREECE	1	0	1
14	HUNGARY	0	1	0
15	ICELAND	1	0	0
16	IRELAND	1	0	0
17	ITALY	1	0	0
18	KOSOVO	0	1	1
19	LATVIA	0	1	0
20	LITHUANIA	0	1	0
21	NORTH MACEDONIA	0	1	1
22	MONTENEGRO	0	1	1
23	NETHERLANDS	1	0	0
24	NORWAY	1	0	0
25	POLAND	0	1	0
26	PORTUGAL	1	0	0
27	REPUBLIC OF MOLDOVA	0	1	0
28	ROMANIA	0	1	1
29	SERBIA	0	1	1
30	SLOVAKIA	0	1	0
31	SLOVENIA	0	1	1
32	SPAIN	1	0	0
33	SWEDEN	1	0	0
34	SWITZERLAND	1	0	0
35	TURKEY	1	0	1
36	UNITED KINGDOM	1	0	0
	European developed countries	19		
	Transition countries		17	
	South East European countries			12

Note: When we compare transition countries with Europena developed countries we use as benchmark European developed countires. Comparing the SEE countries with all other countries, we use as benchmark all other countires that are not SEE

Appendix 3

Methodology for recovering the risk

This methodology was used according to Hughes et al. (1996) and Kotter (2006). Managers maximise utility by choosing optima profit and input demand. Let π denote after tax profit. Technology stipulates the production plan of output quantities y, input quantities x, and capital k. The output prices are denoted by p. Managers form beliefs conditional on future states of the world s as interaction with the plan production (y, x, p, k) to determine profit $\pi = (y, x, p, k|s)$. Moreover, they form a subjective distribution of the prevailing states s. Therefore, this creates the conditional probability distribution of profit to be realised $f(\pi|y, x, p, k, s)$. So, the approach to consider risk would be by defining utility as expected profit and its standard deviation$U(E(\pi), S(\pi))$. Since this risk modelling would not reveal the source of uncertainty which determines $S(\pi)$, Hughes and Moon (1995) suggested that production plan (y, x, p, k) can influence the utility.

Generalized Managerial Utility function, managers maximise utility $U(\pi, y, x, p, k)$ subject to transformation function of the form $T(y, x, k)$ and the rank preferences of the profit. Let m denote income from sources other than output y. In addition, let t be tax rate on profit so that $p_\pi = 1/(1-t)$depicts the price of after tax profit in terms of before tax profit. Then, nominal before tax accounting profit is given as:

$$p_\pi \pi = py + m - wx \qquad (1)$$

under the assumption of perfect competition in input and output markets. This ensures comparability with the case of the cost efficiency. Therefore, we write Utility maximisation problem:

$$\begin{aligned} &\max_{\pi, x} U(\pi, y, x, p, k) \qquad (2) \\ &s.t. p_\pi \pi + wx = py + m, \\ &s.t. T(y, x, z) \le 0 \end{aligned}$$

Solving this maximisation problem for π and x_i, we get the most preferred profit function and the most preferred input demand function:

$$\pi^* = \pi^*(y, v, m, k) \qquad (3)$$
$${x_i}^* = {x_i}^*(y, v, m, k) \qquad (4)$$

Where v is a vector of the price environment of the bank $v = (w, p, p_\pi)$. The profit function π^* is not necessary a profit maximising one from the traditional approach. It reflects the possibility that managers have different preferences and shows the trade-off managers make. Risk preferences are recovered from observed choices of production plans that banks has made. While the most preferred profit demand function is conditional on risk preferences we use it to estimate the benchmark frontier and to derive efficiency estimates.

Empirical Specification

Since the eq. (1) is not possible to estimate because of the unknown functional form and utility is not observable. However, our concern is the ranking of the production plans and profit function that managers assign given their general preferences depicted by utility function. In the context of banking firm, we estimate most preferred profit function and input demand function to gain insight into the preferences of bank managers. This is done by using the techniques from consumer theory that analysis the preferences for goods on basis of their expenditure and budget data. Hughes and Moon (1995) adopted Almost Ideal Demand System (AID) that was developed by Deaton and Muellbauer (1980) by using some Microeconomics techniques; first, the dual relation between the utility maximisation problem (UMP) and the expenditure minimisation problem (EMP); second, the inverse relation of indirect utility and the expenditure function.

Duality allows restating eq. (1) as minimisation problem:

$$\min_{\pi,x} wx + p_\pi \pi \qquad (5)$$
$$s.t. U^0 - U(\pi, y, x, p, k) = 0,$$
$$s.t. T(y, x, k) \leq 0.$$

$U^0$is the fixed level of utility. Solving the optimisation problem we get most preferred profit $\pi^u(y, v, k, U^0)$ and input demand function $x^u(y, v, z, U^0)$. According to Deaton and Muellbauer (1980) we can substitute the indirect utility function $V(y, v, m, k)$ for $U^0$and then we have optimal demand functions as

$$\pi^u\big(y, v, k, V(y, v, m, k)\big) = \pi^*(y, v, m, k) \qquad (6)$$

$$x^u\big(y, v, k, V(y, v, m, k)\big) = x^*(y, v, m, k) \qquad (7)$$

Where $x^*(\cdot)$ and $\pi^*(\cdot)$ are the demand functions given in eq. (3) and (4) and $V(\cdot)$ depicts the indirect utility function. In the following we use the inverse relationship between indirect utility and the expenditure function, so by substitution we get:

$$py + m = E\big(y, v, k, V(y, v, m, k)\big) \qquad (8)$$

Stating that all expenditure on profit and inputs to attain a given level of utility must be equal total revenue, so, that is to meet the budget constraint. Following, the AID in this case is not used to estimate demanded quantities directly. Instead, here we use Sheppard's Lemma to derive budget shares from the expenditure function. In Hughes et al (1996) they adopted AID and define it as:

$$lnE(\cdot) = lnP + U * \beta_0(\prod_i \mathrm{y}_\mathrm{i}^{\beta_\mathrm{i}})(\prod_j \mathrm{w}_\mathrm{j}^{\mathrm{v}_\mathrm{j}})\, \mathrm{p}_\pi^\mu k \qquad (9)$$

Where $lnP$is the price index employed in the AID. Since the initial suggestion of Deaton and Muehlbauer (1980) many application in the consumer literature used the functional form of a translog for the price index. Therefore, we continue to use a translog functional form for the price index. Moreover, this functional form will allow a comparison with the cost minimising model. So, lnP is defined as

$$lnP = \alpha_0 + \alpha_p \ln \tilde{p} + \sum_i \delta_i \ln y_i + \sum_j \omega_j \ln w_j \qquad (10)$$
$$+\eta_\pi \ln p_\pi + \rho \ln z + \frac{1}{2}\alpha_{pp}(\ln \tilde{p})^2$$
$$+\frac{1}{2}\sum_i \sum_j \delta_{ij} \ln y_i \ln y_j + \frac{1}{2}\sum_s \sum_t \omega_{st} \ln w_s \ln w_t$$
$$+\frac{1}{2}\eta_{\pi\pi}(\ln p_\pi)^2 + \frac{1}{2}\rho_{kk}(\ln k)^2 + \sum_j \theta_{pj} \ln \tilde{p} \ln y_j$$

$$+\sum_s \phi_{ps} \ln \tilde{p} \ln w_s + \psi_{p\pi} \ln \tilde{p} \ln p_\pi + \psi_{pz} \ln \tilde{p} \ln k$$
$$+\sum_j \sum_s \gamma_{js} \ln y_j \ln w_s + \sum_j \gamma_{j\pi} \ln y_j \ln p_\pi$$
$$+\sum_j \gamma_{jz} \ln y_j \ln k + \sum_s \omega_{s\pi} \ln w_s \ln p_\pi$$
$$+\sum_s \omega_{sz} \ln w_s \ln k + \eta_{\pi z} \ln p_\pi \ln k.$$

Note that price of each output is not included. Instead we use an average price $\tilde{p}$. The Hughes et al. (1996) showed that this help to conserve on degrees of freedom. Moreover, income earned per output is not readily available for transition countries.

In the following we derive share equation by applying Sheppard's Lemma to eq. (9). We know that partial derivatives of the expenditure function with respect to goods' price are equal to respective budget shares. Knowing this we substitute the indirect utility function for the given utility U^0 into the derivatives $\frac{\partial \ln E(\cdot)}{\partial \ln w_i}$ and $\frac{\partial \ln E(\cdot)}{\partial \ln p_\pi}$. Substituting (8) into (9) and solving for utility, we get the indirect utility function as:

$$V(\cdot) = \frac{\ln(py+m) - \ln P}{\beta_0 (\prod_i y_i^{\beta_i}) (\prod_j w_j^{v_j})} \qquad (11)$$

The share equation for input demand and profit for a given level of utility are then depicted by:

$$\frac{\partial \ln E}{\partial \ln w_i} = \frac{w_i x_i}{py+m} = \frac{\partial \ln P}{\partial \ln w_i} + v_i[\ln(py+m) - \ln P] \qquad (12)$$
$$= \omega_i + \sum_s \omega_{si} \ln \omega_s + \phi_{pi} \ln \tilde{p} + \sum_j \gamma_{ji} \ln y_i + \omega_{\pi i} \ln p_\pi$$
$$+\omega_{iz} \ln z + v_i[\ln(py+m) - \ln P + \varepsilon_{wi}$$

and

$$\frac{\partial \ln E}{\partial \ln p_\pi} = \frac{p_\pi \pi}{py+m} = \frac{\partial \ln P}{\partial \ln p_\pi} + \mu[\ln(py+m) - \ln P] \qquad (13)$$
$$= \eta_\pi + \eta_{\pi\pi} \ln p_\pi + \psi_{p\pi} \ln \tilde{p} + \sum_j \gamma_{j\pi} \ln y_j + \sum_s \omega_{s\pi} \ln w_s$$
$$+\eta_{\pi z} \ln k + \mu[\ln(py+m) - \ln P] + \varepsilon_{p_\pi.}$$

According to the model in Deaton and Muehlbauer (1980) the parameters on consumed goods' prices are defined as:

$$\omega_{si} = \frac{1}{2}(\omega_{si}^* + \omega_{is}^*) = \omega_{is} \quad and \quad \omega_{s\pi} = \frac{1}{2}(\omega_{s\pi}^* + \omega_{\pi s}^*)$$

Moreover, several restrictions are imposed on the model due to symmetry and homogeneity:

$$\delta_{ij} = \delta_{ji} \; and \; \omega_{si} = \omega_{is} \; and \; \omega_{s\pi} = \omega_{\pi s} \text{ for all } i, j, s \; and \; \pi. \qquad (14)$$

The following restriction are:

$$\sum_j v_j + \mu = 0, \qquad (15a)$$

$$\alpha_p + \sum_j \omega_j + \eta_\pi = 1, \qquad (15b)$$

$$\alpha_{pp} + \sum_t \phi_{jt} + \psi_{j\pi} = 0, \qquad (15c)$$

$$\phi_{pt} + \sum_s \omega_{st} + \omega_{t\pi} = 0, \qquad (15d)$$

$$\theta_{pj} + \sum_t \gamma_{jt} + \gamma_{j\pi} = 0, \qquad (15e)$$

$$\eta_{\pi\pi} + \psi_{p\pi} + \sum_s \omega_{s\pi} = 0, \qquad (15f)$$

$$\psi_{pk} + \sum_s \omega_{sk} + \eta_{\pi k} = 0, \qquad (15g)$$

$$\frac{1}{2}\alpha_{pp} + \frac{1}{2}\sum_s\sum_t \omega_{st} + \sum_t \phi_{pt} + \frac{1}{2}\eta_{\pi\pi} + \psi_{p\pi} + \sum_s \omega_{s\pi} = 0. \quad (15h)$$

To impose homogeneity we have to divide all prices by one of the goods' price. For simplicity the Kotter (2006) suggests the price of physical capital. The last of restriction we need because the share derived from dual function must sum to one. The following restrictions are:

$$\sum_i \omega_i + \eta_\pi = 1, \qquad (16a)$$

$$\sum_i \omega_{si} + \omega_{s\pi} = 0, \qquad (16b)$$

$$\sum_i \phi_{pi} + \psi_{p\pi} = 0, \qquad (16c)$$

$$\sum_i \gamma_{ji} + \gamma_{j\pi} = 0, \qquad (16d)$$

$$\sum_i \omega_{\pi i} + \eta_{\pi\pi} = 0, \qquad (16e)$$

$$\sum_i \omega_{ik} + \eta_{\pi k} = 0, \qquad (16f)$$

$$\sum_i v_j + \mu = 0, \qquad (16g)$$

To impose the adding up restrictions the share equation of demand for physical capital is dropped from system. Thus, we are left with system of three equations. After substituting the price index $\ln P$ from eq. (10) into share equations (12) and (13) and collecting terms, the final system results. The collection of the term can be done with nonlinear seemingly unrelated regression equation (nlSURE). From here we follow Hughes et al. (1996) method and we use eq. 13 to measure expected return and risk. Expected return on equity, ER, is the predicted profit divided by financial capital, $= \frac{E(p_\pi \pi)}{k}$. Whereas, expected risk, R, is measured as a standard error of the predicted profit, $S(\frac{E(p_\pi \pi)}{k})$.