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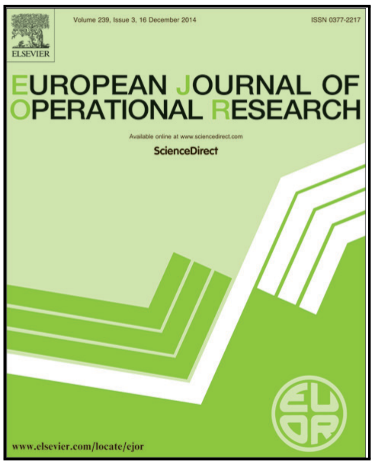

Endogenous Bank Risk and Efficiency

Manthos Delis , Maria Iosifidi , Mike G. Tsionas

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Highlights

- We develop a model to incorporate bank risk within a model of frontier efficiency.
- We model bank risk from the variance of profits or returns.
- We estimate our model using panel data for U.S. banks and Bayesian techniques.
- Excluding risk from the efficiency model significantly biases efficiency estimates.
- There is a negative risk-efficiency nexus with causality running both ways.

Endogenous Bank Risk and Efficiency

Manthos Delis
Department of Finance and Accounting, Surrey Business School, University of Surrey
Guildford, Surrey, GU2 7XH, UK
Email: m.delis@surrey.ac.uk
Telephone number: +44 (0)1483 68 6332

Maria Iosifidi
Department of Finance and Accounting, Surrey Business School, University of Surrey
Guildford, Surrey, GU2 7XH, UK
Email: m.iosifidi@surrey.ac.uk

Mike G. Tsionas
Lancaster University Management School
Lancaster, LA1 4YX, UK
Email: m.tsionas@lancaster.ac.uk

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Abstract

We develop a framework to incorporate bank risk, as measured from the variance of profits or returns, within a model of frontier efficiency. Our framework follows the premise that risk is endogenously related to efficiency. We estimate our model using panel data for U.S. banks and Bayesian techniques. We show that excluding risk from the efficiency model significantly biases the efficiency estimates and the ranking of banks according to their competitive advantage. We also demonstrate that there is a negative risk-efficiency nexus with causality running both ways, while our estimates of risk are fully consistent with the developments in the banking industry over the period 1976-2014.

Keywords: OR in banking; Stochastic frontier; Endogenous risk; Risk-efficiency relationship; Bayesian methods

1. Introduction

Is there a causal relationship between the riskiness and efficiency of banks? And if yes what is the direction of causality? The goal of this paper is to develop a framework that incorporates risk as an endogenous variable into an empirical model of operational efficiency. We use the well-established stochastic frontier approach (SFA), under which the stochastic term of a production, cost, profit, or return function is decomposed into an efficiency-related component and the remainder disturbance.[1] We show that our framework allows the robust estimation of bank efficiency and risk, as well as the identification of the potency and direction in the risk-efficiency nexus.

There are two novel elements of our framework. First, in line with the standard finance literature (e.g., Markowitz, 1952, and many others henceforth), we model risk as the variability of the difference between actual and expected profits (returns). In doing this, we abstain from including specific variables reflecting only certain aspects of risk as inputs/outputs in the production of banking services and allow risk to be estimated in a more thorough way. Second, and quite important, we allow our risk and efficiency estimates to be endogenous to each other. This is an essential improvement of efficiency models given the well-established theoretical proposition that bank risk-taking is endogenous to the characteristics of the specific banking firm, including managerial decision-making, and does not solely emerge out of context (Hughes, 1999; Danielsson and Shin, 2003).

Theoretically, causality between risk and efficiency can run both ways. On the one hand, bank managers seek new risky projects to innovate and differentiate from rival banks, as well as manage existing risk through diversification with the ultimate goal being to

[1] A competitive approach to the stochastic frontier modeling framework is the use of linear programming techniques, mainly Data Envelopment Analysis (DEA). Although DEA methods have advanced to incorporate a stochastic structure, which was the traditional drawback relative to the SFA, the inclusion of risk in DEA remains quite difficult given the requirement to incorporate stochastic assumptions with respect to the volatility of returns. We do, however, propose in the conclusions some possible extensions to incorporate stochastic risk within a DEA framework. For a review in using stochastic DEA methods, see Olesen and Petersen (2016), and for DEA methods in banking, see Fethi and Pasiouras (2010).

increase their revenue (Sharpe, 1964). In contrast, banks pursuing projects with very high risk, given inputs and outputs of production, would experience increased risk and inability to differentiate so as to achieve maximum returns. Thus, we expect both positive and negative forces defining a relation running from risk to profit (return) efficiency.

Conversely, under the impulse of the prospect and the behavioral theories, banks with relatively low efficiency levels are likely to take very high risks. This can be due to effort to catch up with rival banks, slow learning or ineffective risk management, and adaptation (Fiordelisi et al., 2011). For the same reasons, banks with efficient risk management are likely to exhibit good performance as well as low risk-taking. In a similar fashion, successful managers seek new operational structures and technologies to improve operational efficiency in the cost side and contain everyday operational risk. Based on the above arguments, a potential negative relation between risk and return, i.e. the Bowman (1980) paradox, can also be studied as a risk-efficiency nexus.

The above theoretical arguments imply that *bank efficiency and risk are endogenously determined*. We note that most of the empirical efficiency literature does not include a risk component and, when it does, *this risk component is neither formally modelled from the variance of profits nor is endogenously determined by efficiency* (e.g., Dong et al., 2016; references therein). We empirically demonstrate that failing to do so leads to biases in the estimates of efficiency and the competitive advantage of banks versus one another.

In this paper, we extend the SFA by formally building and estimating a four-equation vector autoregression (VAR) model. The first equation retains the standard profit or return function of the SFA, while the second is a stochastic equation differentiating between actual and expected profits (or returns), the variance of which is our measure for risk. The third equation models the contemporaneous level of risk as a function of lagged efficiency (and other determinants) and the fourth equation models efficiency as a function of lagged risk (and other determinants). Given that our model relies on quite a few latent variables (including risk and efficiency), we use Bayesian estimation methods organized around Markov Chain Monte Carlo (MCMC).

We estimate our model using a panel of large U.S. banks that fully compete on a national scale over a period of almost 40 years (1976-2014). The banking industry is ideal for our setting, given the special role of risk, the extensive literature on SFA in banking (e.g., Berger, 2007; references therein), and the availability of longitudal data over a large time span. However, our model can be applied to any other industry for which relevant data are available.

Our results suggest that the average level of estimated efficiency of banks is significantly lower (inefficiency is higher) when we incorporate risk into the SFA. Also, the ranking of banks based on their level of efficiency, and thus the identification of their relative competitive advantage, is also significantly different from the model without risk or from the model where risk is exogenous. Thus, the failure to include risk into the SFA and/or treating risk as an endogenous variable results in erroneous inference about both the absolute level of efficiency and the relative competitive advantage of banks.

Equally important, our findings demonstrate a strong *negative* relationship between risk and efficiency running both ways (from the previous period's risk to current levels of efficiency and vice versa). In this respect, our findings are consistent with the literature following the Bowman (1980) paradox. Our findings are also consistent with the implications of banking literature on important matters, such as the identification of risky periods closely following the historical episodes of financial turmoil and the positive effect of bank capital on risk.

Our results further motivate our paper from a managerial perspective. To the extent that the findings generalize to other industries, the estimation of efficiency while formally incorporating risk as an endogenous variable can better inform firms that compete domestically or internationally about their competitive advantages and their sources. The example of the comparison of the U.S. and Japanese automotive industries by Chen et al. (2015) is particularly apt, as the risky strategic decisions of managers should offer an explanation for the divergence in the efficiency of the two industries. This line of research should also have important implications for recent endeavors to measure the efficiency of the public sector (e.g., Doumpos and Cohen, 2013; Haelermans and Ruggiero, 2013; Galariotis et al., 2016), energy sector (e.g., Fragkiadakis et al. (2016), as well as for cases in which some of the outputs impose negative social externalities (e.g., Chen and Delmas, 2012).

Our work is also related to a strand of finance literature suggesting that any measurement of risk should consider its endogeneity (Danielsson and Shin, 2003; Brunnermeir and Sannikov, 2014; Delis et al., 2015). This literature stresses that the consideration of risk as exogenous within any market or industry and across different measures (e.g., from simple accounting ratios, the net present value calculated by the discounted cash flow method or economic value added, and/or value-at-risk models) produces erroneous estimates and inferences.

The remainder of the paper is organized as follows. Section 2 presents and further motivates our model. Section 3 discusses the empirical application to the banking industry and presents the empirical results. Section 4 concludes the paper.

2. The framework

2.1. Profit and return efficiency

The estimation of firms' operational efficiency is a very popular practice in the operations research and economics literatures (e.g., Lozano-Vivas and Pasiouras, 2010; Kumbhakar and Lovell, 2000). The merit of frontier efficiency measures compared to the traditional accounting-based measures of firm performance is that the former can identify the competitive advantage of a firm *vis-à-vis* its competitors (see the extensive discussion by Chen et al., 2015). In turn, the robust identification of competitive advantage and its sources (from e.g., superior cost management or profitable innovation) has unique implications for managerial efficiency, goals, and strategies.

The most comprehensive measures of frontier efficiency, and the ones used here, are based on profit or return on investment (also called return to outlay). The reason is that these measures incorporate both revenue effects (of producing at inefficient levels) and cost effects (of producing using an inefficient input mix). Under the assumption that firms maximize profits given a production set, the objective function of the firm is:

$$\{ \qquad \}. \tag{1}$$

In (1), *Π* is the profit level of a firm at a specific point in time. In turn, *x* and *y* denote vectors of inputs and outputs of production, with their prices being the vectors and , respectively. This is the alternative profit function (e.g., Lozano-Vivas, 1997), which assumes that firms maximize profits by adjusting output prices and input quantities (as opposed to output and input quantities under the standard profit function). The main reason that this function has become popular in empirical research is the relative lack of information on output prices, especially for multi-output firms. However, an important merit of this approach is that it also allows for the estimation of profit (or return) functions in industries that deviate from perfect competition (Berger and Mester, 1997; Lozano-Vivas and Pasiouras, 2010; Lozano-Vivas, 1997).

The objective function in (1) assumes that all firms produce at an optimal (ideal) profit frontier. Of course, this assumption is quite problematic because all firms produce with some level of inefficiency on either the cost or revenue side. To identify the level of inefficiency, the usual practice (e.g., Kumbhakar and Lovell, 2000) is to estimate an equation of the form:

, (2)

where is the vector of outputs and input prices of firm *i* at time *t*, *β* are technology parameters to be estimated, is the stochastic disturbance, and is a one-sided error term representing profit inefficiency. Profit efficiency can then be simply calculated as . This model is usually termed the SFA to firm efficiency measurement.

Instead of assuming that firms maximize profit, we can assume that firms maximize return on investments. This assumption might be more intuitive from a managerial viewpoint because managers are primarily interested not in the absolute level of profit but in the evaluation of the ability of their investments to generate profits. The formal model considers the maximization of the following objective value function:

{—} (3)

where *V* = total revenue/ total cost and the rest are as in equation (1). As opposed to (1), equation (3) has the additional merit of being non-negative, which is important for the estimation because taking logs of profits in (2) can be problematic when firms are in fact realizing losses. Equation (3) is homogeneous of degree one in all prices, non-decreasing in , and non-increasing in . The equivalent of (2) as a return function is obtained simply by replacing *Π* with *V* in (2) and, for expositional brevity, we only provide the model for profits.

2.2. Endogenous risk in the model of efficiency

The basic SFA analyzed above does not consider the formal inclusion of a risk component. A number of studies, especially in the banking industry where risk deserves special attention (e.g., Mester, 1996; Hughes, 1999), recognize this omission and consider risk in the estimation of efficiency models via the inclusion of specific risk-related variables in the objective function of the bank along with inputs, outputs, and associated prices. This practice is, of course, correct provided that one or a finite number of risk measures (e.g., capital, non-performing loans, etc.) fully control for the riskiness of the bank. Here, we instead propose the estimation of risk within the SFA from the variability of profits or returns, in a manner fully consistent with management, finance, and economics theory (since at least Markowitz, 1952).

Even more notably, this paper represents the first effort to consider the potential endogeneity between risk and efficiency within the well-established SFA. Theoretically, the relation between risk and efficiency in banking can go both ways. To make profits and create value for the banking firm, bank managers seek investments with the highest possible net present value and manage risk in their portfolios to achieve a maximum. Thus, both the level of risk and risk-diversification ability affect the future efficiency and performance of the bank and this is the essence of the well-established positive risk-returns relation (Sharpe, 1964). Further, banks seek to attract new customers and achieve monopolistically competitive profits through risky product innovation and differentiation from competition. Achieving these objectives given a fixed set of inputs and input prices, would also imply that these banks will appear more efficient in the future period.

A relation running from risk to efficiency can, however, be negative due to two main mechanisms. The first is the presence of a shock that increases bank risk exogenously (what Berger and DeYoung, 1997, refer to as the "bad luck hypothesis"). In this case, the increased risk emerges from increases in non-performing assets (loans and securities), the limited ability to securitize or sell these assets, and increases in adverse selection (concerning the screening of new projects) and moral hazard (monitoring of existing projects). Second, the prospect and behavioral theories posit that firms with low performance (low profit and return efficiency in our case) might seek higher risks in an effort to catch up with competition,

ˆ ˆ (A.27)

where

ˆ [‾] [‾ ‾] (A.28)

ˆ [‾]

[ ] ˆ [ˆ] ˆ [ˆ]

where and have a particularly simple form.

Conditional posterior of

This is given by:

‾ ( ) [ ] (A.29)

where ∑ ∑ ∑ ∑ , and . The maximum ˆ of (A.29) can be located by standard univariate optimization techniques, under the assumption that the prior is:

(A.30)

Although this is not essential, if the maximum is interior we can compute

and propose a draw ˆ restricted to the interval (-1, 1). Relative to the existing draw , the new draw is accepted with Metropolis-Hastings probability:

{ ˆ ˆ } (A.31)

We have not encountered cases where the maximum of (A.29) occurs on the boundary.

Part C

In this part we take posterior analysis in the class of models defined by VAR:

(A.32)

where [ ] . For all observations we can write the panel VAR in (A.32) as:

(A.33)

which is in the form of multivariate regression as in (A.26) and therefore coefficients , and can be drawn following the procedure in (A.27) and (A.28).

The conditional posterior distribution of is given by:

(A.34)

where , [ ], , assuming (A.33) is written in the general form:

(A.35)

The prior is assumed. Drawing the exponential components and , as in Section B, can be performed without modifications. Drawing the remaining latent variables is changed as follows.

Conditional posterior of

(A.36)

where and are the typical components of and defined in (A.34) and (A.35). Notably: [ ], [ ] and . Our strategy is to locate the maximum and Hessian of (A.36) and propose a normal draw, which is accepted using the analogous necessary modification of (A.14).

Conditional posterior of

This is given by

$$— (\quad) \quad — \tag{A.37}$$

where appears in both and . We use again a Metropolis-Hastings step and the model and Hessian of (A.37) as in the previous case of .

Conditional posterior of

Relative to (A.20) we now have the extra term:

$$\tag{A.38}$$

and appears in . The most convenient in our case is to propose a draw as in (A.20) and use (A.38) or the Metropolis-Hastings acceptance probability relative to the existing draw . However, a more efficient algorithm resulted by combining (A.20) and (A.38), is to find the mode and Hessian and proceed using an overall Metropolis-Hastings step.

Other numerical details

Our MCMC relies heavily on locating the mode and second derivative for a particular conditional posterior, denoted generically by . In all cases, we use a quasi-Newton algorithm with numerical derivatives to perform the computation. This is done during the transient or burn-in phase, which is tested for convergence using Geweke's (1992) diagnostics.

After the burn-in, to minimize computational costs we use one Gauss-Newton iteration away from the existing draw. In the case of the VAR model in (A.32) we find it more effective to maximize jointly with respect to and form a joint proposal to substitute univariate proposals from (A.36)-(A.38). Relative to the other schemes, this resulted in faster convergence and lower autocorrelations at lag 50. Replacing in this case the Gauss-Newton iteration with an algorithm that relies on full convergence did not provide significantly different performance and the results were mixed when the procedures were applied to subsets of the original data set.

Appendix B. Computation of Bayes factors

In the computation of Bayes factors the role of marginal likelihood is critical. If is a kernel posterior distribution, then the marginal likelihood is $\int$, where is a structural parameter vector. For a number of models whose posterior distributions are , the marginal likelihoods are $\int$ and the Bayes factors against, say, model 1 are given as:

In this paper we use two ways to compute Bayes factors. First, following Verdinelli and Wasserman (1995), given a model whose posterior distribution is , a restricted model corresponding to can be evaluated based on the Bayes factor given by $\int$, where the denominator provides the value of the prior distribution of and the numerator can be computed as $\int$ $\sum$ given the MCMC draws { }. This approach can be used to test stochastic volatility models against their EGARCH counterparts by testing .

This approach cannot be used always for non-nested models.[10] In general, the kernel posterior distribution has the form , where is the structural parameter vector and denotes the latent variables, like the collection of and . If all normalizing constants are included in the components of the kernel posterior, then we have the factorization:

$$\int \int \qquad \int \int$$

Often the conditional distributions have a simple form and their normalizing constants are available in closed form. From MCMC we have a sequence of draws { }, which converges in distribution to the posterior whose kernel is given by . Therefore, { } . From these results we can approximate the marginal likelihood as follows:

$$\sum \int$$

Since the inner integral is not available in closed form, the marginal likelihood is approximated as:

$$\sum$$

where $\sum$ is the posterior mean of the latent variables, a point of high posterior probability mass. This approach makes it possible to approximate marginal likelihoods and Bayes factors easily and without large computational costs.

Appendix C. Results from additional sensitivity tests

In the tables of this Appendix, we report the results from additional sensitivity tests on the VAR model. In Tables C1 and C2, we include more variables (measured at the bank-year

[10] For a general discussion see DiCiccio et al. (1997).

level) in the vector z in equations (6) and (7). Specifically, we use *size* (measured by the natural logarithm of total assets), *liquidity* (the ratio of liquid assets to total assets), *provisions* (the ratio of loan-loss provisions to total loans) and *market share* (the ratio of a bank's assets to the total bank assets in a given state). In Tables C3 and C4, we use the Fourier functional form

Table C1
Empirical results from the VAR model with additional variables included as z in equations (6) and (7): Profit function

	posterior mean	posterior s.d.	posterior mean	posterior s.d.
	0.542	0.020	0.211	0.010
	0.302	0.112	0.212	0.002
	0.148	0.020	0.106	0.122
Time trend	0.012	0.005	-0.030	0.014
EQ/TA	0.068	0.039	0.169	0.002
Size	0.105	0.091	0.014	0.011
Liquidity	-0.047	0.010	0.125	0.048
Provisions	0.081	0.008	0.018	0.003
Market share	0.040	0.059	-0.022	0.038
u	0.115	0.046		

Notes: The table reports the results (posterior mean and standard deviation) obtained from the estimation of equations (4)-(7) using Bayesian maximum likelihood and Markov Chain Monte Carlo. We report only the results from the determinants of stochastic volatility σ and inefficiency u, i.e. equations (6)-(7). We estimate a profit function and the functional form for (4) is the translog.

Table C2
Empirical results from the VAR model with additional variables included as z in equations (6) and (7): Return function

	posterior mean	posterior s.d.	posterior mean	posterior s.d.
	0.419	0.019	0.294	0.015
	0.511	0.123	0.389	0.017
	0.201	0.039	0.148	0.185
Time trend	0.008	0.009	-0.011	0.046
EQ/TA	0.095	0.015	0.082	0.021
Size	0.081	0.090	0.009	0.018
Liquidity	-0.035	0.027	0.111	0.061
Provisions	0.070	0.006	0.023	0.005
Market share	0.030	0.061	-0.016	0.090
u	0.180	0.041		

Notes: The table reports the results (posterior mean and standard deviation) obtained from the estimation of equations (4)-(7) using Bayesian maximum likelihood and Markov Chain Monte Carlo. We report only the results from the determinants of stochastic volatility σ and inefficiency u, i.e. equations (6)-(7). We estimate a return function and the functional form for (4) is the translog.

Table C3
Empirical results from the VAR model: Profit function (Fourier)

	posterior mean	posterior s.d.	posterior mean	posterior s.d.
	0.510	0.016	0.194	0.008
	0.320	0.129	0.183	0.002
	0.103	0.021	0.093	0.140
Time trend	0.009	0.006	-0.027	0.016
EQ/TA	0.073	0.036	0.152	0.002
u	0.125	0.040		

Notes: The table reports the results (posterior mean and standard deviation) obtained from the estimation of equations (4)-(7) using Bayesian maximum likelihood and Markov Chain Monte Carlo. We report only the results from the determinants of stochastic volatility σ and inefficiency u, i.e. equations (6)-(7). We estimate a profit function and the functional form for (4) is the translog.

Table C4
Empirical results from the VAR model: Return function (Fourier)

	posterior mean	posterior s.d.	posterior mean	posterior s.d.
	0.487	0.014	0.301	0.009
	0.482	0.105	0.452	0.019
	0.169	0.022	0.126	0.215
Time trend	0.006	0.010	-0.009	0.025
EQ/TA	0.089	0.010	0.082	0.020
u	0.188	0.044		

Notes: The table reports the results (posterior mean and standard deviation) obtained from the estimation of equations (4)-(7) using Bayesian maximum likelihood and Markov Chain Monte Carlo. We report only the results from the determinants of stochastic volatility σ and inefficiency u, i.e. equations (6)-(7). We estimate a return function and the functional form for (4) is the translog.

Table 1
Summary statistics

Variable	Mean	Median	Std. dev.	Min.	Max.
logΠ	9.16	9.01	1.31	1.09	15.57
logV	0.21	0.20	0.30	-5.57	3.58
	2.25	2.19	0.68	-0.17	5.56
	2.63	2.58	0.61	0.69	4.54
	1.10	1.17	0.43	-0.24	2.20
	13.70	13.35	1.19	5.12	20.29
	12.50	12.33	1.37	1.54	19.22
EQ/TA	11.71	11.36	1.15	7.92	18.44
Number of obs.	15,922	15,922	15,922	15,922	15,922

Notes: The table reports summary statistics for the main variables used in the empirical analysis. All variables are in natural logarithms. Π is profits before taxes; V is the ratio of total revenue to total cost; w_1 is the ratio of expenditures on fixed assets to premises and fixed assets; w_2 is the ratio of personnel salaries divided by the number of full-time equivalent employees; w_3 is interest expenses on deposits and interest expenses on fed funds divided by the sum of total deposits and fed funds purchased; y_1 is total loans; y*2* is total securities; and EQ/TA is the ratio of total equity to total assets.

Table 2
Posterior results from the basic model for the volatility equation

	Profit function		Return function	
	Posterior mean	Posterior s.d.	Posterior mean	Posterior s.d.
	0.214	0.098	0.121	0.015
	0.324	0.120	0.518	0.102
	0.131	0.057	0.044	0.002
Time trend	0.007	0.007	0.004	0.013
EQ/TA	0.040	0.032	0.007	0.022
u	0.147	0.035	0.171	0.107
JB test	0.302		0.415	

Notes: The table reports the results (posterior mean and standard deviation) obtained from the estimation of equations (4)-(6) using Bayesian maximum likelihood and Markov Chain Monte Carlo. We report only the results from the determinants of stochastic volatility σ, i.e. equation (6). We estimate models by alternatively using profit and return functions. The functional form for (4) is the translog. The variables are defined in Table 1 and u represents inefficiency. JB test is the p-value of the Jarque-Bera tests for normality.

Table 3
Empirical results from the VAR model: Profit function

	posterior mean	posterior s.d.	posterior mean	posterior s.d.
	0.617	0.022	0.221	0.011
	0.315	0.116	0.225	0.002
	0.151	0.026	0.117	0.116
Time trend	0.011	0.004	-0.032	0.012
EQ/TA	0.071	0.043	0.181	0.001
u	0.117	0.048		
JB test	0.364		0.259	

Notes: The table reports the results (posterior mean and standard deviation) obtained from the estimation of equations (4)-(7) using Bayesian maximum likelihood and Markov Chain Monte Carlo. We report only the results from the determinants of stochastic volatility σ and inefficiency u, i.e. equations (6)-(7). We estimate a profit function and the functional form for (4) is the translog. The variables are defined in Table 1 and u represents inefficiency. JB test is the p-value of the Jarque-Bera tests for normality.

Table 4
Empirical results for the VAR model: Return function

	posterior mean	posterior s.d.	posterior mean	posterior s.d.
	0.453	0.014	0.315	0.017
	0.556	0.104	0.401	0.015
	0.212	0.026	0.155	0.201
Time trend	0.009	0.007	-0.013	0.038
EQ/TA	0.102	0.021	0.077	0.025
u	0.185	0.124		
JB test	0.484		0.360	

Notes: The table reports the results (posterior mean and standard deviation) obtained from the estimation of equations (4)-(7) using Bayesian maximum likelihood and Markov Chain Monte Carlo. We report only the results from the determinants of stochastic volatility σ and inefficiency u, i.e. equations (6)-(7). We estimate a return function and the functional form for (4) is the translog. The variables are defined in Table 1 and u represents inefficiency. JB test is the p-value of the Jarque-Bera tests for normality.

Figure 1
Annual averages of downside risk from the profit and return VAR models