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Assessing cost efficiency and economies of scale in the European banking system, a Bayesian stochastic frontier approach

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ASSESSING COST EFFICIENCY AND ECONOMIES OF SCALE IN THE EUROPEAN BANKING SYSTEM, A BAYESIAN STOCHASTIC FRONTIER APPROACH

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This dissertation is dedicated to my family and friends.

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Table of Contents

Abstract

Cost efficiency of banks is a key indicator that provides valuable insight to researchers and policymakers about the functioning of the financial intermediation process, as well as, the overall performance of the entire financial system.

This thesis focuses on the cost efficiency of the European banking market for which we identify fourteen nation-specific frontiers and also perform cross country comparisons under a common frontier assumption. Our interest in the subject is twofold. At the nation level, cost efficiency influences the relative competitiveness of banks, setting the profile of the national banking industry with direct implications on economic growth. At the European Union level, the financial, institutional and regulatory integration raise questions about the existence of a common cost frontier or the presence of economies of scale as they could encourage banks to take advantage of the single market and consolidate.

The empirical approach uses a more general Bayesian stochastic frontier model that allows for a continuous shift from the individual frontiers of each country to the common "European" frontier through varying priors.

Results show differences in the frontiers of the countries that we studied, and the selected banks exhibit economies of scale greater than one more often than not, irrespective of size.

Chapter 1
Introduction

The global character of the recent recession that followed in the wake of a profound financial crisis has dramatically reaffirmed the existence of a highly interdependent and sophisticated world financial system. At the same time, the crisis sends a clear signal that an accurate and intimate understanding of the mechanism, as a whole, is vital in order to ensure coordinated and consistent actions on the part of all key system participants. In an increasingly globalized and integrated World, where economic and financial realities transcend national borders, policymakers also need to secure an appropriate vantage point.

In the case of the European Union (EU) these aspects are particularly relevant and topical. A political and economic community of 27 countries, the EU represents the world's largest economy,[1]. It functions as a hybrid system of supranational independent institutions[2] in which decisions are made inter-governmentally and they are jointly agreed upon by the member states.

The European Union must ensure the free movement of people, goods, services, and capital and also have a common currency area for a subset of 17 countries, while preserving 27 distinct national identities.

[1] As of 2010, measured by total nominal Gross Domestic Product (GDP).

[2] Some of the key European Institutions include: the European Commission, the European Parliament, the European Central Bank, and the Court of Justice of the European Union.

Under these circumstances, the requirement to maintain a single market poses significant challenges and raises unique questions regarding the economic and political coordination along several key dimensions.

One issue of particular interest to European policy makers is the performance and degree of integration of European System. As Berger (2007) was pointing out, cross-country comparisons have often produced contradictory results and each of the two main approaches have their own drawbacks.

One popular solution among the empirical studies is to pool together the data from different countries and identify a common frontier. Each country's average efficiency level is estimated relative to a shared frontier. By doing so, this approach implicitly ignores the differences in the legislative, economic and cultural reality across countries and may lead to biased results.

A second group of researchers analyzes the efficiency at the level of each country by developing individual country frontiers based on each nation's bank data. Unfortunately, analysis of the relative efficiencies is rendered difficult by the lack of a shared reference frontier in this approach.

The third category of studies that Berger identifies looks at the differences in efficiency levels between foreign owned and domestically owned banks within the same country. The fact that they face the same frontier makes the comparison possible, but we don't actually see two banking systems being compared in this case.

This dissertation uses Bayesian methods applied to stochastic cost frontier models in order to illustrate both the nation-specific and the common frontier approaches and also presents a hybrid model that nests both models.

There are a small number of studies that compare the efficiency of Eastern European banking systems to their Western counterparts and in for this reason, we included in analysis countries from the Eastern European block that either entered the EU or have applied. For a selected group of banks we estimate economies of scale.

In our study we utilize Bureau van Dijk database of banks' balance sheet and income statement data for 14 European national banking markets from 2001 through 2009. The dissertation provides an empirical analysis of the technologies employed by banks in these 14 nations and the efficiency of the banks.

Chapter 2 of the dissertation is a short overview of Bayesian analysis and stochastic frontier models while chapter 3 presents the related banking literature. In chapter 4 we make a detailed presentation of the data used. Chapter 5 presents the single frontier methodology, results and conclusions. In chapter 6 we develop the common frontier, report the results and draw conclusions. In chapter 7 we present the more general model that nests the previous two approaches with results and conclusions while chapter 8 summarizes and concludes our research and also talks about future research ideas.

Chapter 2
Theoretical Background

2.1 Bayesian Analysis

2.1.1 Introduction

The Bayesian paradigm can be understood as a rationalist theory that studies personal beliefs in the context of uncertainty and yields normative propositions that prescribe how an individual should act in order to avoid certain kinds of undesirable behavioral inconsistencies. As Bernardo and Smith (1994) argue, the Bayesian framework lends itself naturally to Economics where "the expected utility maximization provides the basis for rational decision making and [...] Bayes' Theorem provides the key to the ways in which beliefs should fit together in the light of changing evidence."

From a technical point of view, the Bayesian approach is closely related to likelihood methods; likelihood functions provide the basis for both classical and Bayesian statistical inference. However under the Bayesian approach data is combined with "prior" knowledge, incorporated in a formal manner, to produce posterior probability distributions for the parameters of interest. Specifically, the researcher's original beliefs, in the form of the assumed priors for the parameters, are updated through a feedback mechanism, via Bayes' Theorem, while taking into account the data.

Mathematically, a Bayesian estimate of a parameter is derived as the value that minimizes the posterior expected loss function. This parameter depends both on the loss function employed, and on the assumed prior distribution. The probabilistic interpretation assigned to parameters is specific to Bayesian analysis and it is the main distinguishing feature from the non-Bayesian methods.

Jaynes (1985) concisely describes the Bayesian approach to statistical estimation as follows:

> In Bayesian parameter estimation, both the prior and posterior distributions represent, not any measurable property of the parameter, but only our own state of knowledge about it. The width of the distribution is not intended to indicate the range of variability of the true values of the parameter. To the contrary, it indicates the range of values that are consistent with our prior information and data, and which honesty therefore compels us to admit as possible values. What is "distributed" is not the parameter, but the probability.

The Bayesian methodology can be seen as a set of theoretical and practical techniques for quantifying uncertainty in inferences using probability models, statistical data analysis and an optimal information processing rule - Bayes' Theorem - that serves as the focal point of Bayesian inference. Zellner (1988) explains that Bayes' Rule uses efficiently all the available information in the data, without adding any extraneous information and it "allows prior information to be employed in a formal and reproductive manner".

The basic building blocks of the Bayesian data analysis process are summarized as follows:

- Modeling - Specify the full probability model as a joint probability distribution for all observable and unobservable quantities. In this step the researcher coherently combines information from data, with objective knowledge from theory and subjective knowledge in the form of prior distributions specified for the parameters;

- Estimation - Make conditional probabilistic statements regarding the parameterization of the model by calculating and interpreting the appropriate posterior distribution.

The conditioning is made with respect to the structure of the model and the observed data that combine to form the likelihood function, which is linked via Bayes' Rule to the prior distribution of the parameters and yields the associated *posterior distribution.*

- Analysis - Evaluate the fit of the model and the conceptual implications of the posterior distribution obtained in the estimation stage. In particular, the researcher is concerned with the critical evaluation of the inferred conclusions, their sensitivity to the modeling assumptions made and how well the model fits the data.

2.1.2 Bayesian versus Non-Bayesian Approach - Costs and Benefits

A very compelling benefit of the Bayesian approach, that sets it apart from the traditional frequentist paradigm, is that it provides a unified treatment of inference and decision making, while accounting for both parameter and model uncertainty. In this sense, the Bayesian literature argues that Bayesian inference "provides the benefits of exact sample results, integration of decision-making, estimation, testing, model selection and a full accounting of uncertainty", Rossi et al. (2007).

While frequentist inference makes exclusively pre-sample[1] probability assertions, providing confidence intervals that bracket the true value of the parameter only in the long run, with a given frequency, Bayesian inference delivers answers that are conditional on the observed data as opposed to the distribution of estimators or test statistics over theoretical, unobserved, samples.

Bayesian inference, thus, helps characterize uncertainty about parameter values given the actual, observed, sample, serving as a guide to decision making.

[1] A 90% confidence interval brackets the true value of the parameter with probability .90 only before the sample has been observed, after the probability is either zero or one.

For instance, under the Bayesian paradigm the researcher can make probabilistic statements whether the parameter is in one region versus another, which is not possible in the frequentist approach. Also, the Bayesian methodology can be applied to cases where the frequentist definition of probability, as a long run relative frequency, proves infeasible, such as for unique once-and-for-all phenomena or uncertain past events.

Another attractive benefit of using Bayesian methods follows from the fact that they deliver, by integrating out the nuisance parameters, a finite sample posterior density which can then be used to derive optimal, finite sample estimates of the parameters of interest and make exact finite sample probability statements about their possible values. Moreover, Bayesian econometrics allows the direct computation of many complicated functions of the underlying parameters, while capturing, in these objects, all the existing uncertainty regarding the parameter values.

Integrating out the nuisance parameters is mathematically equivalent to averaging over the conditional posterior densities of the desired parameters, given the nuisance parameters. In the frequentist approach this is not possible and, the usual practice is to instead use estimates of the nuisance parameters and give the resulting "operational" estimator an asymptotic justification.

Bayesian methods generally yield exact finite sample results in many cases where non-Bayesian methods have difficulties in producing optimal finite sample estimators or test statistics with known distributions and, instead, they have to resort to approximate, large sample, inference techniques. Examples of such situations include among others: cointegrated time series models, generalized method of moments problems, selection bias models, and simultaneous equations model problems.

Furthermore, the Bayesian approach delivers good asymptotic results for both i.i.d. and stochastically dependent observations, (see for example Jeffreys, 1998). It also has the added benefit that the assumptions needed to derive asymptotic normality of posterior densities centered at the maximum likelihood estimate are, in the case of the stochastically dependent observations, weaker than those required for the asymptotic normality of the maximum likelihood estimators.

Finally, Bayesian data analysis deals in a natural way with misspecified models (see Monfort, 1996). Bayesian econometricians are mainly concerned with finding a good description of the data. Thus, in this case the estimation transforms from being a process of researching some 'true' parameter values, into a selection instrument in the parameter space that enhances the researcher's ability to use the model as a language for expressing the regular features of the data.

In a sense, the Bayesian approach emphasizes more the 'normality' of lack of identification, than the problems it creates. While, it is possible with Bayesian methods to always achieve identification using non-flat priors, mechanical identification is not a goal in itself, and rather, as Manski (1999) put it, the researcher needs to be concerned with "what conclusions can and cannot logically be drawn given empirically relevant combinations of assumptions and data" - a principle that is subsumed in the Bayesian paradigm.

Regarding the costs of the Bayesian approach, the critiques raised in the non - Bayesian literature generally focus on three aspects: the necessity to specify priors, the difficulties associated with the use of a likelihood function and the computational burden the researcher faces in obtaining posterior distributions for the parameters of interest.

While the first and the last of these disadvantages apply specifically to Bayesian methods, the limitations[2] imposed by the likelihood function requirement are shared with the maximum likelihood methods and.

Although, non-trivial these disadvantages are generally seen as of secondary importance for a Bayesian exercise, considering that the integration of an even high dimensional function,

[2]The likelihood equations have to be specifically worked out for a given distribution and estimation problem. Often the numerical estimation is computationally intensive, and the philosophical background is less well established, especially in terms of probabilities and statistical measures of unique historical events

with potentially many flat surfaces, is, in some settings, considerably more tractable than its maximization.

The requirement to specify a prior distribution for all unknown quantities in the model (parameters and missing data[3]) has brought several objections from non-Bayesian econometricians. The frequentist proponents present the choice of the prior as a limiting factor to the objectivity of the scientific approach and criticized the lack of robustness of the Bayesian procedures for their reliance on computationally convenient priors and the use of specific priors in cases where that data and prior would conflict.

While the debate is still ongoing, the Bayesian (and even some of the non-Bayesian) econometricians bring into question the objectivity of the frequentist inference. They point out that the assumptions made in the frequentist approach, for instance in the model formulating stage, introduce, informally, in the data analysis process considerable subjective information, that reflects in fact the researcher's prior beliefs.

In this sense, Tukey (1978), a non-Bayesian statistician, starkly emphasizes the normality of having prior beliefs, be it formal or informal, in statistic analysis:

> It is my impression that rather generally, not just in econometrics, it is considered decent to use judgment in choosing a functional form, but indecent to use judgment in choosing a coefficient. If judgment about important things is quite all right, why should it not be used for less important ones as well?

Furthermore, concerning the importance of priors in the Bayesian approach, Zellner (2000) points out that Bayesian econometricians use diffuse (non-informative) and informative prior densities quite broadly. For hierarchical models, state space models, random effects models, and random initial conditions for time series models, the distributions are introduced for parameters that are actually "part of the model" and drawing a direct connection between the priors used and the results of the estimation is, at best, an oversimplification.

[3]Allowing the data to play a role in determining the prior distribution characterizes the, so called, empirical Bayes approach.

Finally, the computational advances in the 1990s, coupled with the software development and implementation of various MCMC simulation techniques, have all but eliminated the constraints on priors and models, and have greatly simplified the calculation of posterior distributions. Although the robustness of the Bayesian methods, like of any other econometrical approach for that matter, could still be seen as a fundamental issue in the academic debate, their technical tractability no longer appears as a substantiated concern.

2.1.3 Bayes' Theorem

Bayes' theorem serves as the cornerstone of Bayesian statistics. It can be characterized as an optimal information processing rule that uses efficiently all the available information to obtain the posterior distribution of some unknown parameters, by combining in a formal and reproductive manner, prior information with sample information summarized by the likelihood function.

Let y be a random variable that is observed and θ be an unknown parameter drawn from some distribution $p(\theta)$. From the definition of conditional probability it follows that:

$$\Pr(\theta|y) = \frac{\Pr(y, \theta)}{\Pr(y)}. \tag{2.1}$$

Moreover, the joint probability $\Pr(y, \theta)$ can be written using the definition of conditional probability again, as follows:

$$\Pr(y, \theta) = \Pr(y|\theta)\Pr(\theta) \tag{2.2}$$

.

Substituting equation (2.2) in (2.1) gives equation (2.3), the univariate version of Bayes' theorem.

$$\Pr(\theta|y) = \frac{\Pr(y|\theta)\Pr(\theta)}{\Pr(y)} \tag{2.3}$$

where $\Pr(\theta)$ is the prior distribution of the possible θ values and $Pr(\theta|y)$ is the posterior distribution of θ given the observed data y.

Alternatively, in the continuous multivariate case, Bayes' Theorem has the following form:

$$p(\Theta|y) = \frac{p(y|\Theta)p(\Theta)}{p(y)} = \frac{p(y|\Theta)p(\Theta)}{\int p(y,\Theta)d\Theta} \tag{2.4}$$

where $\Theta = (\theta^{(1)},\ \theta^{(2)},\ \cdots,\ \theta^{(k)})$ is a vector of k (potentially) continuous variables, $p(\Theta)$ is the assumed prior distribution of the unknown parameters, $p(y|\Theta) = \ell(\Theta|y)$ is the likelihood function, and $p(\Theta|y)$ is the posterior distribution given the prior of the unknown parameter(s) $p(\Theta)$ and the data y.

Since in equation (2.4) the term $1/p(y)$ is essentially a constant (with respect to Θ), the posterior distribution can be written as:

$$p(\Theta|y) \propto \ell(\Theta|y)p(\Theta) \tag{2.5}$$

where the symbol $\propto$ signifies that the posterior distribution is "proportional" (equal up to a constant) to the likelihood augmented with the prior. Also, since the constant $p(y)$ normalizes $p(y|\Theta) \cdot p(\Theta)$ to one, it can be obtained by integration as follows:

$$p(y) = \int_{\Theta} p(y|\Theta) \cdot p(\Theta)d\Theta \tag{2.6}$$

.

The dependence of the posterior on the prior is useful in inferring how much information on the unknown parameter values is contained in the data. In this sense, if the posterior is highly dependent on the prior, then the data likely has little signal.

Alternatively, if the posterior distribution is relatively stable over a choice of priors, the opposite will be true and the data contain significant information. Succinctly, this can be seen by taking logs on equation 2.4 and dropping the normalizing constant:

$$\log(\text{posterior}) \approx \log(\text{likelihood}) + \log(\text{prior}) \tag{2.7}$$

2.1.4 The Choice of a Prior

A defining feature of Bayesian analysis is the choice of a prior. For informative data the posterior distribution is robust over a fairly wide range of priors. With non-informative data the characteristics of the prior used, in particular its location (mean or mode) and precision (the inverse of the variance), become especially meaningful for the resulting posterior distribution. Moreover, the family of the prior distribution is often chosen to simplify the calculation of the posterior - specifically the class of conjugate priors comprises of distributions that for specific likelihood functions give posteriors in the same distribution family[4].

Diffuse Priors

An attractive benefit of the Bayesian methodology is that it can make use, in a formal manner, of any existing information, empirical or theoretical, about the unknown parameters of interest. This preexisting information serves to improve the estimation process and is integrated by adopting appropriate, case specific, prior distributions commonly referred to as *informative priors* for parts, or even the entire, parameter vector Θ.

Alternatively, if such information is not available, or deemed undesirable for the scope of the research, the practice is to use instead *uninformative* or *diffuse priors*.

[4]For example a gamma prior with a Poisson likelihood returns a gamma posterior.

The most common diffuse prior[5] is just a constant, which implies that there is no evidence to justify favoring any particular parameter value over another :

$$p(\theta) = k = \frac{1}{b-a} \; for \; a \; \leq \theta \leq b \tag{2.8}$$

Applying Bayes' Theorem it follows that the posterior distribution is a constant times the likelihood, which can then be written as: $p(\theta|y) \propto \ell(\theta|y)$.

A special situation arises when the parameter of interest has a range over $(0, \; \infty)$ or $(-\infty, \; +\infty)$, because a flat prior does not exist in the strict sense for such cases, since the integral does not exist for any non-zero constant and is instead called an *improper prior*.

The use of diffuse priors is also appropriate for cases when the likelihood exhibits a natural scale; that is the likelihood function has a form such that the data only influences the unknown parameter vector by a translation on the scale of the function. For instance, the likelihood function for a parameter Θ and data vector y can be written in data-translated format as:

$$\ell(\Theta|y) = g\left[h(\Theta) - t(y)\right] \tag{2.9}$$

where $\ell = g(z)$ is the likelihood function with $z = h(\Theta) - t(y)$ and the data y only appears in the sufficient statistic t, such that different values of y with the same value of $t(y)$ have the same likelihood.

The natural scale for the unknown parameter Θ in this case is $h(\Theta)$ and a flat prior on Θ of the form $p\left[h(\Theta)\right] = constant$ or $p(\Theta) \propto |\partial h(\Theta)/\partial\Theta|$ (if transformed using the change of variable method) should be used.

For cases when the natural scale of the likelihood function cannot be easily found, Jeffreys (1998) has proposed a general prior based on the Fisher information I of the likelihood.

[5]It is interesting to note that classical results from frequentist statistics can be obtained using the Bayesian methodology by assuming a flat prior.

The Fisher information has the following form[6]:

$$p(\Theta) \propto \sqrt{\det[I(\theta|y)]} \tag{2.10}$$

with $I(\Theta|y)_{ij}$ given by:

$$I(\Theta|y)_{ij} = -E_y\left(\frac{\partial^2 \ln \ell(\Theta|y)}{\partial\theta_i\partial\theta_j}\right) \tag{2.11}$$

Conjugate Priors

The use of conjugate priors that for specific likelihood functions return a posterior distribution in the same family as the prior distribution allows for analytic tractability. While no longer strictly necessary, thanks to the widespread availability of simulation techniques that will be discussed later in this chapter, they are nevertheless technically convenient. Many commonly used distributions like normal, gamma, exponential, Poisson, or binomial belong to the exponential family, with a general form given by equation (12).

In general, if the likelihood is drawn from the exponential family, a conjugate prior, that is also part of the exponential family, can be found such that the posterior distribution will be similar to the prior, as follows:

Given the likelihood for a single observation (out of n):

$$\ell(y_i|\theta) = g(\theta)h(y)\exp\left(\sum_{j=1}^{m}\phi_j(\theta)t_j(y_i)\right) \tag{2.12}$$

and a prior

$$p(\theta) \propto [g(\theta)]^b \exp\left(\sum_{j=1}^{m}\phi_j(\theta)a_j\right) \tag{2.13}$$

[6]For a full derivation see Lee (1997).

The posterior density is given by:

$$p(\theta|y) \propto \left[\prod_{i=1}^{n} \ell(y_i|\theta)\right] p(\theta) =\propto [g(\theta)]^{b+n} \exp\left(\sum_{j=1}^{m} \phi_j(\theta) d_j(y)\right) \tag{2.14}$$

with

$$d_j = a_j + \sum_{i=1}^{n} t_j(y_i) \tag{2.15}$$

.

In Table 2.1 the conjugate priors for some common likelihood functions from the exponential family of distributions are presented.

Table 2.1: Conjugate Priors for Common Likelihood Functions

Likelihood	**Conjugate prior**
Binomial	Beta
Multinomial	Dirichlet
Poisson	Gamma
Normal	
μ unknown, σ^2 known	Normal
μ known, σ^2 unknown	Inverse Chi-Square
Multivariate Normal	
μ unknown, V known	Multivariate Normal
μ known, V unknown	Inverse Wishart

2.1.5 The Posterior Density Function

In Bayesian econometrics the full estimator for the unknown parameter (vector) of interest is the posterior density function itself. In general, the posterior distribution can be obtained through sampling algorithms such as Metropolis Hastings. The posterior density is often presented as a frequency histogram constructed using samples generated from the posterior distribution.

Alternatively, the posterior distribution can be summarized in a variety of ways, for example:

- Following maximum likelihood, the mode of the distribution can be given:

$$\widehat{\theta} = \max_{\theta}[p(\theta|y)] \tag{2.16}$$

- The expected value of θ given the posterior,$E[\theta|y]$, can be used:

$$\widehat{\theta} = E[\theta|y] = \int \theta p(\theta|y)d\theta \tag{2.17}$$

- Or the median of the posterior distribution can be calculated, such that the estimator satisfies $\Pr(\theta > \widehat{\theta}|y) = Pr(\theta < \widehat{\theta}|y) = 0.5$:

$$\int_{\widehat{\theta}}^{+\infty} p(\theta|y)d\theta = \int_{-\infty}^{\hat{\theta}} p(\theta|y)d\theta = \frac{1}{2} \tag{2.18}$$

Also it is worth noting that Bayesian analysis has the attractive advantage, over the frequentist approach, of being capable to easily produce a (marginal) posterior density for a subset of the unknown parameters by integrating out the nuisance parameters in the posterior density function. For example, if the vector of the unknown parameters Θ is partitioned into two parts $\Theta = (\Theta_1, \Theta_2)$, where Θ_2 represents the vector of nuisance parameters, the posterior distribution for Θ_1 is given by:

$$p(\Theta_1|y) = \int_{\Theta_2} p(\Theta_1, \Theta_2|y)d\Theta_2 \tag{2.19}$$

2.1.6 Posterior Simulation

Obtaining the posterior distribution function can be, in many cases, difficult and computationally intensive, requiring the calculation of high dimensional integrals or sampling from complicated and, often, unknown distributions. Before the remarkable advances in simulation techniques in the 1990s, in particular the development and implementation of Markov Chain Monte Carlo (MCMC) methods, which will be discussed in this section in some detail, the evaluation of the posterior distribution represented the major hurdle in the empirical application of Bayesian analysis.

Initially, Bayesian econometricians had to rely on simple models that proved analytically tractable or they were restricted to using specific priors and likelihood functions, part of the so-called conjugate family that return a known posterior distribution, which attracted significant criticism from the frequentist proponents for the apparent lack of robustness of the Bayesian approach. In an attempt to alleviate the problem, several analytic approximation methods,[7] usually based on normal kernel expansions, were developed to calculate marginals and expectations, but they had the major drawback of being computationally very intensive and time consuming, in many cases requiring two function maximizations.

A major breakthrough and improvement happened in the 1980s, with the advent of non-iterative numerical integration techniques (and also cheaper and more easily available computational power) that delivered exact or approximate posterior distributions. Some of the most widely used approaches were those based on quadrature rules (like Davis and Rabinowitz 1984) and Monte Carlo methods: importance sampling (Geweke 1988, 1989) or sampling/importance sampling (Rubin 1987; Gelfand and Smith 1990).

Nevertheless, an important limitation of the numerical integration techniques mentioned was their inability to deal with higher dimensions.

[7] One of the most widely used was Laplace's method, see DeBruijn (1961).

In the end this was a major factor in the development and introduction in the 1990s of sample based iterative simulation techniques, widely known as MCMC methods. These techniques have proved to be both more efficient and more robust than their counterparts, being capable of producing accurate samples even for high dimensional and complicated posterior distributions.

Direct Simulation

For simple, nonhierarchical Bayesian models, especially if conjugate priors have been assumed, or as a first approximation for more complicated problems, it is often convenient to factor the distribution analytically and simulate it in parts. In general, the distribution of a continuous parameter can be approximated as a discrete distribution on a grid of points, by calculating the target density $p(\theta|y)$ at a set of evenly spaced values $(\theta_1, \cdots, \theta_n)$ that span a broad range of the parameter space for θ.

The continuous $p(\theta|y)$ is then approximated by the discrete density at $(\theta_1, \cdots, \theta_n)$ with probabilities $p(\theta_i|y)/\sum_{j=1}^{N} p(\theta_j|y)$.

Given the computed grid values, a random draw from $p(\theta|y)$ is taken by drawing a random sample U from the uniform distribution on [0,1] and then transforming it, using the inverse cdf method, to obtain a sample from the discrete approximation. This method requires the grid points to be fine enough to cover well the parameter space and for this reason it does not work well for high-dimensional multivariate methods since for such cases the computational cost imposed can easily become prohibitive.

In the class of direct simulation techniques, *rejection sampling* is a widely employed method, which is often used as part of more complex simulation approaches and thus a brief description would prove useful. Given a target density $p(\theta|y)$, rejection sampling requires a positive function $g(\theta)$ defined for all θ where $p(\theta|y) > 0$.

The function $g(\theta)$ needs to satisfy all of the following:

- The function $g(\theta)$ has a finite integral (it does not necessarily have to integrate to one) and random samples can be drawn from the probability density proportional to g
- The importance ratio $p(\theta|y)/g(\theta)$ must have a known, finite, bound M.

The rejection sampling algorithm consists of two steps:

1. Draw a random sample for θ from the probability density proportional to $g(\theta)$
2. Accept θ as a draw from $p(\theta|y)$ with probability[8] $p(\theta|y)/Mg(\theta)$. If the draw is rejected, return to step 1.

The approximate density $g(\theta)$ should be chosen to be roughly proportional to $p(\theta|y)$. Ideally $g \propto f$ in which case, for a suitable value of M, virtually every draw can be accepted with probability one. Alternatively, if that is not the case, the value for the bound M has to be set large enough, such that the acceptance probability in the first step of the algorithm is very low.

Markov Chain Simulation

Markov Chain Monte Carlo (MCMC) simulation refers to a generic class of methods based on drawing values of θ from approximate distributions and then adjusting these draws to better match the target posterior distribution $p(\theta|y)$. These techniques are used when it is not possible (or it is computationally inefficient) to draw θ directly from $p(\theta|y)$ and instead it is more convenient to sample iteratively from a distribution that becomes, with each step, closer to the posterior distribution.

[8]The boundedness condition on the importance ratio ensures that the acceptance probability cannot be larger than one.

Examples of problems that can be solved in the MCMC framework include: intractable posterior distributions for which known generators fail, hierarchical models, censored models, data augmentation and models with missing data.

The basic approach is built around the concept of *Markov chain*, which is defined as a sequence of random variables $(\theta^1,\ \theta^2,\ \cdots,)$ such that, for any t, the distribution of θ^t, conditional on all previous θ's, depends only on θ^{t-1}.

Succinctly, random samples are drawn sequentially forming a Markov chain, with the distribution of the sampled draws depending only on the value drawn. The objective is to create a Markov process whose invariant (stationary) distribution is the target posterior density $p(\theta|y)$ and run the simulation long enough to ensure that convergence is achieved, such that the current draws are arbitrarily close to the stationary distribution.

Gibbs sampler, Metropolis, and Metropolis-Hastings algorithms are representative methods in the class of MCMC techniques that effectively form the backbone of current empirical Bayesian analysis and are each briefly discussed below.

The Metropolis and Metropolis-Hastings Algorithms

Metropolis-Hastings is a generic name for a family of algorithms in the Markov Chain class that includes Metropolis and its generalization Metropolis-Hastings, which are used extensively for constructing and sampling from transition distributions for arbitrary target distributions. While these techniques are applicable to a wide range of problems from various science fields, in Bayesian data analysis they prove particularly valuable for sampling posterior distributions that are difficult or, even impossible, to sample from directly.

The Metropolis algorithm was initially proposed by Metropolis et al. (1953) to study the equilibrium properties of large systems of particles in an atom.

The algorithm is an adaptation of a random walk that uses an acceptance/rejection rule to converge to the specified target distribution. It sequentially samples values of the unknown parameters from an approximate distribution and then corrects the draws to get closer to the target density $p(\theta|y)$, in a similar way to importance sampling with the one exception that in this case the distribution of the draws depends on the previous value drawn, which makes this method a Markov chain.

Briefly the algorithm can be described as follows:

1. Draw a starting point θ^0 from a starting distribution $p_0(\theta)$ typically based on approximation of the target density, such that $p(\theta^0|y) > 0$.

2. For $t = 1, 2, \cdots$

   - Sample a proposal θ^* from a symmetric *jumping (candidate) distribution* $J_t(\theta^*|\theta^{t-1})$, with $J_t(\theta_1|\theta_2) = J_t(\theta_2|\theta_1)$ for all θ_1, θ_2, and t. To ensure the efficiency of the algorithm, the candidate distribution must be easy to sample and convenient for the computation of the ratio r, covers the parameter space reasonably well and has a reasonable rejection rate in the sense that the jumps are not rejected too frequently, so the random walk spends a long time in one place.

   - Compute the ratio of densities:

$$r = \frac{p(\theta^*|y)}{p(\theta^{t-1}|y)} \tag{2.20}$$

   - Set:

$$\theta^t = \begin{cases} \theta^*, \ with\ probability\ min(r, 1) \\ \theta^{t-1}, \ otherwise \end{cases} \tag{2.21}$$

The transition distribution $T_t(\theta^t|\theta^{t-1})$ can be characterized, given the current value for θ^{t-1}, as a mixture of a point mass at $\theta^t = \theta^{t-1}$ and the jumping distribution $J_t(\theta^t|\theta^{t-1})$ adjusted for the acceptance rate.

Metropolis-Hastings is a generalization of the Metropolis algorithm, developed by Hastings (1970), which modifies the basic algorithm in two ways: it relaxes the symmetry requirement on the jumping distribution and, to correct for asymmetry in the jumping rule, it computes r as a ratio of ratios:

$$r = \frac{p(\theta^*|y)/J_t(\theta^*|\theta^{t-1})}{p(\theta^{t-1}|y)/J_t(\theta^{t-1}|\theta^*)} \tag{2.22}$$

The Metropolis-Hastings algorithm, by allowing for asymmetric jumping rules, has the attractive advantage over the classical Metropolis approach of being more efficient and increasing the speed of the random walk and convergence.

The Gibbs Sampler

The Gibbs sampler, sometimes called *alternating conditional sampling*, is another core Markov chain algorithm that is, besides Metropolis-Hastings, extensively used in multidimensional problems. For Bayesian purposes the Gibbs sampler has proved to be particularly useful in dealing with hierarchical models (Seltzer et al. 1996), censored models (Geweke 1992), the seemingly unrelated regression model of Zellner (1962) (Blattberg 1991 and Percy 1992) and models with missing data (Gelfand and Carlin 1993) among others.

Gibbs sampler represents a special case of the Metropolis-Hasting algorithm. Given the parameter vector θ, divided into d subvectors, Gibbs sampler cycles, at every iteration t, through all the components of θ, indexed by j, drawing each subset of parameters conditional on the value of all others θ^{t-1}_{-j}.

The candidate distribution $J_{j,t}(\cdot|\cdot)$ at step j of iteration t only jumps along the jth subvector with conditional posterior density of θ_j given θ_{-j}^{t-1}:

$$J_{j,t}^{\text{Gibbs}}(\theta^*|\theta^{t-1}) = \begin{cases} p(\theta_j^*|\theta_{-j}^{t-1}, y), \ if \ \theta_{-j}^* = \theta_{-j}^{t-1} \\ 0, \ otherwise \end{cases} \tag{2.23}$$

where $\theta_{-j}^{t-1} = (\theta_1^t, \ \cdots, \ \theta_{j-1}^t, \ \theta_{j+1}^t, \ \cdots, \ \theta_d^t)$ represents all components of θ, except for θ_j , at their current values.

The only jumps possible are to parameter vectors θ^* that match θ^{t-1} on all components except the jth and the ratio r in this case is given by:

$$r = \frac{p(\theta^*|y)/J_{j,t}^{\text{Gibbs}}(\theta^*|\theta^{t-1})}{p(\theta^{t-1}|y)/J_{j,t}^{\text{Gibbs}}(\theta^{t-1}|\theta^*)} = \frac{p(\theta^*|y)/p(\theta_j^*|\theta_{-j}^{t-1}, y)}{p(\theta^{t-1}|y)/p(\theta_j^{t-1}|\theta_{-j}^{t-1}, y)} = \frac{p(\theta_j^{t-1}|y)}{p(\theta_j^{t-1}|y)} = 1 \tag{2.24}$$

Gibbs sampler and the Metropolis algorithm are useful as preliminary steps for simulating from complicated distributions that complement each other in empirical work. For instance, if there are conditional posterior distributions in a model that can be sampled from directly, while some cannot, then the parameters can be updated one a time using Gibbs sample whenever possible and one dimensional Metropolis algorithm otherwise.

When the scalar parameters are highly correlated with each other, instead of breaking down the parameter vector Θ into its individual components, very often it is practical to block parameters together based on their correlation and update each block using either the Gibbs sampler or a Metropolis jump of the parameters within that block. This practice has the advantage of improving convergence speed, since if the parameters were treated individually, the autocorrelation would decay very slowly, thus requiring a very large number of iterations. The downside of blocking is that it requires drawings from a multivariate distribution, which are technically more challenging to deal with, compared to an univariate distribution.

As for any method in the MCMC class, achieving convergence is a particularly important issue, otherwise the simulations will misrepresent the target distribution and the inference process will be flawed. Furthermore, since the early iterations resemble the starting approximating distribution, it is recommended to use these as burn-in period of the sampler and discard them after convergence has been reached.

A brief outline of some statistical tests commonly used to assess Markov chain convergence is given below:

- Gelman-Rubin Diagnostics - is a one sided test based on a variance ratio test statistic. It uses parallel chains with dispersed initial values to check for convergence to the target distribution and compares the variances within each chain and between chains. Rejection occurs when there are large deviations between these variances indicating nonconvergence, which may be due to a multi-mode posterior distribution or because the burn-in is not yet complete and a longer chain must be run.

- Geweke Diagnostics - is a two-sided test and evaluates convergence by comparing means from the first and latter part of the Markov chain. Large absolute values of the test statistic z indicate nonconvergence.

- Heidelberger-Welch Diagnostics - consists of two parts: a stationarity, one sided, test based on the Cramer-von Mises statistic which tests the hypothesis that the chain comes from a covariance stationary process and a half-width test that checks whether the Markov chain sample size is appropriate. The stationary test can be performed repeatedly on the same chain: if it passes, then the entire chain is considered stationary, alternatively the first 10 percent of the chain is discarded and the test is repeated. The process continues until either the chain passes or there is not enough data remaining to construct a confidence interval. The part of the chain that is considered stationary is then put through the half-width test.

- Raftery-Lewis Diagnostics - is a test designed to find the number of samples needed to reach a desired level of accuracy of the estimated percentiles. The usefulness of this test is limited to percentiles and should not be used to asses the convergence of a chain as a whole. Furthermore, the test is very sensitive to even small changes to input variables such as the desired coverage probability or the cumulative probability of interest. Rejection indicates that a longer Markov Chain is required.

Also another significant issue in the implementation of the Gibbs sampler is the potential interdependence between draws. In order to obtain approximately independent draws from the target distribution one simple practice is to discard every kth draw. Nevertheless, this has a significant negative effect on the efficiency of the process. An alternative to this approach is the multiple path method that requires the researcher to run p parallel simulations, and keep the last value in each sequence. This method has the advantage that it can prove helpful in checking the convergence of the chain by comparing the variances within and between sequences[9], which helps alleviate the efficiency cost that it imposes (only p data points are used out of pn).

2.2 Stochastic Frontier Model

2.2.1 Introduction

The ability to formalize and measure the economic performance of producers is of prime importance, considering the sum of all existing economic processes that ensure the transformation of scarce resources into goods and services required to satisfy the diverse, competing, and virtually unlimited needs and wants of human society.

The economic theory behind efficiency analysis stems from the seminal contributions

[9]If the variance within each sequence is significantly smaller than the variance between sequences suggests that convergence has not been achieved yet.

of Koopmans (1951) and Debreu (1951) on activity analysis. Farrell (1957) is the first empirical work that, building on this theoretical background, has relaxed the classical assumption of perfect input-output allocation and proposed a method to evaluate individual firm (in)efficiency with respect to a benchmark technology given by a frontier function representing efficient operations.

Farrell's approach represents a clear departure from the concept of average firm performance used in the econometric literature on production functions and efficiency of the period. In his framework, efficiency is decomposed into two components: *pure technical efficiency* and *allocative efficiency* that together give the overall level of efficiency, later referred to in the literature as *economic efficiency*.

Pure technical efficiency reflects a firm's ability to minimize the use of inputs for producing a given amount of output and indicates the potential reduction in the use of inputs by adopting the practices of the best-performance firms that are operating on the frontier. Distance functions (Shephard 1953, 1970) can be used to study this type of efficiency by measuring the distance of a given productive activity to the boundary of production possibilities.

Allocative efficiency refers to the plant's capacity to operate at its most efficient size by using inputs in optimal proportions conditional on input prices and their marginal productivities.

Contingent on the behavioral assumptions made about the productive unit analyzed, alternative representations of the structure of production technology can be generated using duality theory in the form of cost, revenue and, respectively, profit frontiers which then define the relative level of economic efficiency for a particular activity or unit.

In practice, efficiency measurement implies, at a basic level, the comparison between an indicator of the actual performance of a productive unit or activity and an empirical approximation of the “best-practice” frontier. Depending on the method used to derive this reference frontier, two main and competing estimation techniques can be distinguished in the literature on efficiency measurement: *the mathematical programming approach* and *the econometric approach*.

The mathematical programming approach or Data Envelopment Analysis (DEA) is non-parametric and relies on mathematical linear programming to construct piecewise linear segments of the best performance benchmark frontier from the observed data on inputs and outputs, yielding a convex Production Possibility Set.

The theoretical fundaments of DEA stem from the seminal work of Farrell (1957), later extended by Banker, Charnes and Cooper (1984), and Färe, Grosskopf, and Lovell (1985).

The widespread application of DEA techniques in empirical work began with the contribution of Charnes, Cooper and Rhodes (1978) that proposed an input oriented model and assumed constant returns to scale (CRS). The CRS assumption implies that all firms analyzed are operating at an optimal scale which, taking into account imperfect competition and financial constraints, is overly restrictive and may lead to an incorrect measure of (pure) technical efficiency. Banker et al. (1984) have subsequently extended the original model to allow for variable returns to scale (VRS).

In general under the DEA method it is possible to measure technical inefficiency either as a proportional reduction in input usage to produce a certain output (an input-oriented model) or as proportional increase in output given the existing input usage (an output-oriented model). Although the two types of models estimate the same frontier and identify the same set of efficient firms, they may give different efficiency measures, if the CRS assumption does not hold.

An important criticism raised against the DEA models stems from their non-stochastic nature and refers to the difficulty of drawing statistical inference. Most studies assume that any deviation from the frontier function is due to technical inefficiency, thus ignoring the effect of any sampling noise on the efficiency of the estimators, leading to potentially misleading conclusions.

As Simar and Wilson (1998) point out, the inherent complexity of the DEA estimators for a multi-output, multi-input analysis further complicates the issue, leaving bootstrapping as virtually the only feasible way to investigate the sampling properties of these estimators and compute confidence intervals. Nevertheless, simulating the data generating process is still a difficult endeavor, especially in the context of DEA, which requires the nonparametric estimation of the boundary of a high dimensional object.

The econometric approach, as opposed to DEA, is stochastic and, at the expense of having to make assumptions regarding the functional form of technology and inefficiency, allows for statistical inference.

The analytical foundations of Stochastic Frontier Analysis lie in the works of Aigner, Lovell and Schmidt (1977), Meeusen and van den Broeck (1977) and Battese and Corra (1977) who simultaneously, and independently, developed a Stochastic Frontier Model (SFM).

The SFM features a composed error structure. Part of the error term models the inefficiency component, typically represented as a one sided distribution.

The other component of the error term captures the effect of exogenous shocks (statistical noise), usually assumed to be normally distributed with mean zero.

Generically the stochastic frontier production function can be written as follows:

$$y_i = f(x_i, \beta) + \epsilon_i, \tag{2.25}$$

where y_i is the observed output, x_i is the vector of inputs, β is a vector of unknown parameters and $\epsilon_i = u_i - v_i$ is the composite error term. The error component u_i represents statistical noise and it is typically assumed to be distributed independently and identically as $u_i \sim N(0, \sigma_u^2)$, while v_i denotes technical inefficiency and $v_i \geq 0$ thus all observed outputs lie either on or below the stochastic frontier.

In the recent years, the distinction between DEA and the econometric approach has become much less clear cut thanks to new methods that make use of flexible functional forms, semiparametric and Bayesian techniques. These new applications reduce both the risk of misspecification arising from a rigid parameterization and, at the same time, alleviate the limitation of non-parametric estimation, providing a basis for statistical inference. As Fried et al. (2008) put it, "the gap is no longer between one technique and the other, but between best-practice knowledge and average practice implementation"

2.2.2 Stochastic Cost Frontier

Cost inefficiency is a mix of both technical and allocative inefficiency, and this makes its estimation technically more involved than that of a stochastic production frontier. Formal analysis of allocative inefficiency requires, besides more detailed data (information on input prices, output quantities, total expenditure on inputs and, potentially, input quantities and input cost shares) the estimation of a cost frontier based on an input oriented approach.

In particular, the use of an input oriented approach in the estimation of the stochastic cost frontier implies that inputs no longer have to be treated equally, and thus knowledge of quasi-fixed inputs can be used to derive a variable cost frontier instead.

The most important difference, though, stems from the ability to decompose cost inefficiency, as opposed to pure technical inefficiency associated with production frontier, into input-oriented technical inefficiency and input-allocative inefficiency.

This can be particularly informative if there are different causes for the two inefficiencies.

Furthermore, cost efficiency cannot be greater than input oriented technical efficiency[10] (since input efficiency is a necessary condition for cost efficiency) with the difference representing input allocative efficiency.

2.2.3 The Bayesian Stochastic Cost Frontier

The basic Stochastic Frontier framework with a composite structure of the error term representing deviations from a theoretical frontier. It was originally introduced by Meeusen and van den Broeck (1977) and Aigner, Lovell and Schmidt (1977). The model has been extended by van den Broeck, Koop, Osiewalski, and Steel (1993) to incorporate Bayesian methods. They argued that this new approach had several distinct advantages over the classical methods. Most notably, it allowed the computation of exact finite sample results for any parameter of interest and it also provided a very intuitive framework for model comparisons. Initially they applied the method on an empirical example about electric utility companies (cross sectional data) taken from Greene (1990), using Monte Carlo integration with importance sampling.

Later, Koop, Osiewalski, and Steel in another 1993 paper refined the approach by using Gibbs sampling instead[11] to obtain a random sample from a joint distribution by taking random draws from only conditional distributions. This was motivated by technical factors, because the importance sampling integration proved to be computationally demanding and thus not very well suited for the study of more involved research problems.

Another important theoretical contribution was made by Koop et al. (1993), who derived conditional densities for the stochastic frontier model for various different sampling distributions on the efficiency term: exponential as in Meeusen and van den Broeck (1977),

[10] Also, estimates of input oriented technical efficiency are not necessarily the same with estimates output oriented technical efficiency.

[11] Simple Monte Carlo integration was also suggested as a possible alternative to Gibbs sampling.

half-Normal of Aigner, Lovell, and Schmidt (1977), truncated Normal of Stevenson (1980), and gamma as in Greene (1990).

With a focus on Bayesian stochastic cost frontier analysis, Terrell (1996) proposed an approach for imposing monotonicity and concavity restrictions on the set of prices where inferences are drawn. The flexible form cost functions considered are translog, generalized Leontief and symmetric generalized Leontief.

In 1997 the method was extended and applied by Koop et al. (1997) and Fernandez, Osiewalski and Steel (1997) to the measurement of economic efficiency in panel data models, where technical inefficiency is assumed to be time invariant. Lewis and Anderson (1998) and Lewis, Springer and Anderson (2003) considered the case when mean economic inefficiency differs across two groups.

More recently, using a Bayesian approach on a translog cost system, Kumbhakar and Tsionas (2005) proposed a solution to the so-called "Greene problem"[12] in a random effects framework.

[12] Estimating technical and allocative inefficiency for a translog cost function (Greene, 1980) is challenging as the translog functional form has many variables and they tend to exhibit multicollinearity.

Chapter 3
Related Banking Literature

3.1 Comparisons of Banking Efficiency Across Countries

Starting with the seminal contributions of Aigner, Lovell and Schmidt (1977) and Meeusen and van den Broek (1977) in the field of stochastic frontier models, over the past three decades, there has been a veritable explosion in the number of empirical studies on firm efficiency and productivity.

In particular, there is a very fast growing body of literature which focuses on banking efficiency. The interest in the banking industry is largely motivated by the pivotal role, within an increasingly (globally) integrated financial system, played by commercial banks in the efficient allocation of financial resources that has strong implications on the functioning of the entire economic mechanism.

Furthermore, it is particularly important, from a policy making point of view, to understand and evaluate potential vulnerabilities of the domestic banking system, as well as foreign banking systems, especially considering the stability aspect of the global financial system.

A comprehensive review[1] of the banking efficiency literature, given its remarkable richness, goes beyond the scope of this dissertation. Instead, we focus on highlighting the research specialized in international comparisons of banking efficiency that is closely related to our work and research agenda as it was summarized by Berger (2007). He classifies the banking literature based on how the bank comparisons were conducted in three logical categories:

(1) comparisons of the efficiencies of banks in different nations using a common frontier;

(2) comparisons of the efficiencies of banks in different nations using the same nation-specific frontier for all domestic banks;

(3) comparisons of the efficiencies of foreign-owned versus domestically owned banks within a nation, using a common, nation-specific, frontier.

The first of the three categories subsumes a large number of studies that share a common approach regarding the efficient frontier found at the heart of the analysis; specifically this is made of the best performing banks in the entire data set, regardless of nationality. Statistics, such as average bank efficiency are then calculated and used to perform comparisons across nations.

One of the early papers, representative for this batch, is Berg, Forsund, Hjalmarsson and Suomien (1993) that studies commercial banks' efficiency in Norway, Sweden and Finland using Data Envelopment Analysis (DEA). The authors argue that, on average, Swedish banks are more efficient than the ones from Norway or Finland.

The dominance of Swedish banks was confirmed later by Buck, Berg and Forsund (1995) and Bergendahl (1995) in efficiency studies that also add Denmark to the mix..

An important caveat of these early cross-country studies is that they do not control, rigorously, for differences in economic environment across nations.

[1]For a more detailed study of the literature and measurement methods see for example Berger and Humphrey (1997) and Berger (2007) on which the presentation from this section is based.

Most of them implicitly assume that the differences in banking efficiency can only arise from different managerial practices and technologies available to the banking industry in each country.

Essentially this eliminates any potential role for prudential supervisory and regulatory requirements, market conditions, population density, quality of banking services provided or competition for inputs and outputs in affecting the banks' cost and profit performance. These kind of environmental factors, besides having a logical connection to how banks conduct their business, arguably manifest significant more heterogeneity across countries, especially, when compared to things like the underlying technologies of the banking services production which, for developed countries at least, should be fairly similar.

If it is indeed the case that country-specific variables are important in explaining efficiency differences, performing an efficiency analysis based on a common frontier, in the absence of appropriate controls, will tend to overestimate the inefficiency levels, making cross-country comparisons suspect and difficult to interpret.

Furthermore, another, more general, limitation concerning the international comparability of bank efficiency based on the common frontier approach is that, from a conceptual point of view, a measure of the efficiency of domestic banks within their own borders is not necessarily appropriate for characterizing their performance as foreign-owned institutions in another country. Even without significant regulatory or economic differences, between the domestic and foreign economy, an otherwise efficient bank might still face significant difficulties in operating in a different country.

At empirical level some of these issues have become apparent, when studies started producing contradicting results. For instance, Fecher and Pestieau (1993) applied DEA and Distribution Free Approach (DFA) to 11 OECD countries including Sweden and Norway and found that average bank efficiency in Norway is higher than in Sweden, effectively reversing the ranking suggested by Berg et al. (1993).

Also according to their results, U.S. banks appear to be relatively inefficient, holding the second-lowest average efficiency among the 11 countries studied. This finding is again puzzling and was challenged by other studies such as: DeYoung and Nolle (1996), or Hasan and Hunter (1996), who argue that foreign-owned banks in the U.S. are in fact significantly less efficient than domestic banks.

In an attempt to address some of the limitations of the early research outlined above, later studies have introduced better controls to account for differences in economic environments. One of the earliest attempts was made by Allen and Rai (1996), who use Distribution Free Approach (DFA) and Stochastic Frontier Analysis (SFA) to carry out a banking efficiency comparison across 15 developed countries, characterized by different regulatory environments.

Accounting for regulatory differences, Allen and Rai (1996) distinguish between universal banking countries that permit the functional integration of commercial and investment banking and separated banking countries that do not. They measure the inefficiency levels in each group, and investigate for potential regularities by regressing bank specific inefficiency measures against various bank and market characteristics.

Typically, the controls introduced refer to banking market conditions, such as population, deposit and branching densities, regulations (risk, average equity capital ratio) and market structures. For instance, Dietsch and Lozano-Vivas (2000) look at the French and Spanish banking industries and control for three categories of environmental variables: the main macroeconomic which determine the banking products demand characteristics conditions, the structure and regulation of the banking industry, and the accessibility of banking services.

Their results show that the Spanish banks seem to suffer excess costs, or structural disadvantages, compared to French banks, in order to adjust to environmental differences, such as a lower density of population, a lower income level of their customers and a lower rate of financial intermediation.

Similar studies include Lozano-Vivas, Pastor, and Hasan (2001), Lozano-Vivas, Pastor, and Pastor. (2002), and Kwan (2003) among others.

The critique regarding the bias induced by environmental differences when using a common frontier can be, at least conceptually, alleviated to a certain degree when discussing about banking systems in a group of countries characterized by relatively similar economic conditions. While this approach might be easier to justify in the case of a union of nations; like the European Union (e.g. Casu and Girardone (2006), Barros, Ferreira, and Williams (2007), or Maudos and de Guevara (2007)), it has also been used for transition economies of Eastern Europe (e.g. Bonin, Hasan, and Wachtel (2005), Yildirim and Philippatos (2007)) or for countries in Southeast Asia (e.g. Hollo and Nagy (2006)).

The recent research, in this category, has taken an increasingly more critical approach regarding the validity of the common frontier assumption in efficiency analysis. For instance, Bos and Kolari (2005) estimate both common and separate frontiers for European and U.S. banks and test the hypothesis that banks operate under the same cost and profit frontiers. Their results confirm a common profit frontier, but not a cost frontier. In a similar spirit, but only for Europe, Bos and Schmiedel (2007) investigate the existence of a single Western European banking market using data on the commercial banking systems for 15 European countries. Their methodology follows Battese, Rao, and O'Donnell (2004), and they argue based on the stochastic meta-frontier results that conventional estimates using common frontiers tend to underestimate cost and profit efficiency.

The second broad research category covers studies that focus on measuring the efficiency of banks within a single nation against a best practice frontier determined for that particular data set. Motivation wise, most of these single-nation studies address policy relevant issues concerning the effects on banking efficiency of bank regulation (like DeYoung 1998), institution size or organization form (Hermalin and Wallace 1994 and Tulkens, 1993), sources of productivity changes (Berger and Mester 2003), etc.

An important limitation of this approach is that it can only provide information regarding the efficiency dispersion of banks within a country; it is not tractable to perform multinational relative comparisons since each country is evaluated from the perspective of its nation-specific frontier. Furthermore, like the first method, it does not include a mechanism to measure efficiency advantages/disadvantages of a foreign-owned bank relative to domestic banks.

While the policy implications, nation-wise, are still significant, this leaves out important, topical, research and policy questions regarding the international expansion of financial institutions, limiting the potential scope of these studies. Nevertheless, this method can still shed some light on other topics such as the degree of market power or bank competition that exists between countries. For instance, Berger, Hasan, and Klapper (2004) evaluate the economic effects of the relative efficiency of community banks versus other banks using data from 21 developed nations and 28 developing nations.

Finally, in terms of broadly quantifying the general level of scientific interest in the field, according to the statistics given by Berger and Humphrey in their 1997 survey, this particular area of research appears to enjoy considerable popularity: with 116 single country studies analyzing banking activity in 21 different countries. While the U.S. and the Western European countries were particularly well represented, and continue to be so in the more recent studies, the number of countries investigated has been increasing steadily such that at the present time virtually all developed nations are represented.

The last category of literature compares the efficiency of foreign-owned versus domestically-owned banks operating in the same nation based on a common, nation-specific, frontier. This method measures the ability of banks to operate in foreign countries and it specifically targets banks that are operating internationally.

Regarding the reasons why a certain bank may decide to expand its activity abroad, a potential efficiency advantage for such foreign-owned banks is that this would allow the subsidiary bank to continue and strengthen their business relationship with corporate agents, who are already its customers. The result would be that the subsidiary bank has a dedicated clientele and access to a new market, while the multinational customer enjoys the continued benefit of a prolonged and, potentially, advantageous banking relationship with a specific banker.

The empirical evidence in this sense is mixed: on the one hand there are studies that suggest that at least some banking organizations do engage in the "follow your customer" strategy by setting up offices in nations in which their home nation corporate customers have foreign affiliates (e.g. Grosse and Goldberg, (1991); Ter (1995)), while, on the other hand, there is evidence indicating that foreign-owned banks may not cater primarily to firms headquartered in the home nation, and instead tend to focus mostly on other business borrowers (for e.g. Seth, Nolle, and Mohanty,1998).

Another potential efficiency advantage that can justify entering a foreign banking market, is risk diversification across nations and regions of the world. A reduction in risk and an increase in the bank's financial stability may raise profits through a decrease in the cost of capital and risk management. While multinational evidence is limited, studies on banks' geographical diversification within the U.S (such as Hughes, Lang, Mester, and Moon (1996)) and bank mergers and acquisitions (e.g. Akhavein, Berger, and Humphrey (1997)) show substantial financial gains.

Furthermore, foreign-owned banks may also have an efficiency edge over domestic banks, particularly in developing countries characterized by a large number of state-owned banks in the system, in terms of managerial expertise and experience , access to capital, or ability to make large loans. Supporting evidence is provided by studies such as: Barth, Caprio, and Levine (1999) or Berger, Hasan, and Klapper (2004).

In terms of the efficiency disadvantages faced by foreign-owned banks studies such as Buch (2003), Buch (2005), Choi, Francis, and Hasan (2006) and Buch and DeLong (2004) suggest that environmental factors like distance, culture, and high regulation tend to deter cross border mergers and acquisitions. Berger and Udell (2002) and Stein (2002) also argue that some of these foreign owned institutions are at a disadvantage because of the "sof" information about local conditions.

In terms of the comparability, at international level, of the research on the efficiency of foreign-owned versus domestically owned banks, results are quite mixed. Studies that use U.S. banking data generally find that foreign-owned banks are significantly less efficient on average than domestic banks (e.g., DeYoung and Nolle, 1996; Hasan and Hunter, 1996, Hasan, and Hunter, 1998).

Papers using data on banks in other developed nations typically argue that foreign-owned banks are roughly as efficient as domestically owned banks (e.g.,Vander 1996; Hasan and Lozano-Vivas, 1998) or, in some cases, more efficient (Sturm and Williams, 2004). Results are not differentiated by the nation of origin of the foreign-owned banks, neither in the case of the US, nor of the other developed countries, thus limiting their applicability.

Regarding the developed nations, the most comprehensive studies use multiple nations and identify the nation of origin of the foreign-owned banks. Their results generally suggest that foreign-owned banks are, on average, less efficient than domestically owned banks. However, foreign-owned banks headquartered in the U.S. are often more efficient than domestically owned banks in many nations (e.g., Berger, DeYoung, Genay, and Udell, 2000). The exact reasons for the relative success of U.S.-owned banks are still open to debate.

3.2 Notes on European Banking Systems

The Single European Act was signed in February 1986 and came into effect in July 1987. Later, it served as the foundation of the Single Market Project that was developed and introduced in a stepwise manner by the end of 1992. For banks, this translated into an EU-wide banking permit, commonly referred to as the "European passport". The introduction of the Euro (in 1999 only as an accounting currency and then in circulation starting with 2002) followed up by the European Union's action plan to create an integrated market for financial services by 2005, opened the national markets and allowed for increased cross-border competition.

Theoretically, in an environment that is expected to become more competitive, the efficient banks have a better chance of survival. They can also take advantage of the wider market (benefiting from economies of scale). At the same time, the inefficient players can expect to become targets of takeovers/mergers. Nevertheless, the historical evidence[2] regarding the financial integration in the European Union is fairly mixed.

In the first years after the adoption of the Euro, banks and banking markets appeared to consolidate especially at the local level with a very limited number of cross-border mergers (Berger et al. 2003). Subsequently, there was a significant increase in cross-border mergers and acquisitions, and a large share of these operations involved western European banks acquiring stakes in other western European banks according to a 2006 Pricewaterhouse Coopers report[3]. In the wake of the financial crisis, complicated by the more recent sovereign debt troubles [4] the focus appears to have shifted yet again towards the national markets.

[2] Goddard et al. 2007

[3] http://www.pwc.com/en_GX/gx/banking-capital-markets/pdf/banking_consolidation.pdf

[4] Citing data released by the European Banking Authority in London, Bloomberg provides a list of European banks with at least 500 million euro sovereign debt exposure http://www.bloomberg.com/news/2011-12-08/european-banks-sovereign-debt-exposure-by-country-table-.html

3.2.1 Germany

Germany is a founding member of the European Union and is part of the Eurozone since its official launch in January 1999. Germany has a developed economy and financial system, being the largest economy, by nominal GDP, in the EU area and the fourth largest in the world.

Germany's banking system, as characterized by Krahnen and Schmidt (2004), is represented by three "pillars": private commercial banks, public sector banks, and cooperative banks, that can be further differentiated by the ownership structure and business orientation. Overall, there are a large number (1,919 in 2010) of credit institutions that comprise the system.

Privately owned commercial banks are the largest group, in terms of assets, with 36 percent of the total banking system assets. As of 2010 this segment includes: three large banking groups (two domestic and one foreign), medium and small-sized banks and branches of foreign banks. The large banking groups operate as universal banks, while the other banks tend to be more regionally-focused.

The group of public sector banks, that includes savings banks (Sparkassen), comes next with a 31 percent share of total banking assets. The general mandate of these banks is to support regional economic development, subsidize local public goods and offer financial services for the German public. They tend to have a well-developed network serving a diverse customer base providing a complex selection of banking services, with a particular focus on retail and small- and medium-sized enterprises.

A large group of cooperative banks, which are typically small, but very numerous, account for approximately two thirds of the total number of credit institutions operating in Germany. The cooperative banks provide regular banking services to the general public.

Their main characteristic is that they are owned by their members, who are also their most important clients (both as depositors and borrowers) representing roughly half of their operations. Also, these banks operate under a mutual guarantee scheme and have a regional focus. While the basic structure of the system has remained largely unchanged, the German banking sector has experienced a significant amount of consolidation since 1990. The number of banks in Germany has decreased by 44 percent. The process was concentrated especially in the savings and cooperative sectors with the explicit purpose of attaining economies of scale. The consolidation continued in the recent years, partly fueled by the financial difficulties induced by the crisis, with some operations being of a cross-border nature. A particularity of the system is the high level of public involvement, which is significantly larger than in many other EU countries.

The effect of the financial crisis on the German banking sector was significant, mainly due to exposures to toxic assets. A number of institutions, especially commercial and savings banks experienced difficulties and required financial help. The Government implemented various relief programs and has successfully managed the situation, stabilizing the German financial sector.

3.2.2 France

France has, after Germany, the second largest economy by nominal GDP in the European Union. It is one of the original six founding states of the European Economic Community, the forerunner of the current EU, and is also member of Eurozone from its onset, in January 1999.

The French banking system is dominated by a relatively small number of large universal banks offering a diverse selection of banking services, which suggests a high degree of consolidation.

In terms of assets, the nine largest banks cumulate approximately 75 percent of total assets, while the first five banks are responsible for more than half of total deposit and lending operations.

Regarding the ownership, the private commercial banks dominate the system - the combined value of their assets being roughly five times larger than that of mutual and cooperative banks together. Also, at the moment, foreign banks are not very well represented in retail banking, with the possible exception of HSBC, but tend to have a stronger presence in wholesale banking and securities trading.

According to France's leading bank supervision institution, Autorité de Contrôle Prudentiel (ACP), in January 2011, there were 678 credit institutions authorized to operate in the country. These can be broadly classified into three categories: general-purpose credit institutions, specialized credit institutions and investment service providers. The legal framework governing the activity of these entities is compatible with the Union requirements, with over 70 percent of banking regulations being European in origin.

In January 2011, there were 370 general-purpose credit institutions registered with ACP. This category includes commercial banks, as well as, mutual and cooperative banks that are licensed to perform any type of banking operation. This includes foreign exchange activities, transactions with precious metals, consulting services and equity investment.

The specialized credit institutions are typically restricted to a subset of banking services decided by their level of authorization. For instance, the 18 municipal credit banks operating in 2011 specialize in the issuance of pledge loans, while the financial companies (287, as of January 2011) usually focus on one of the following broad types of activities: consumer loans or corporate loans, lease financing, factoring, and guarantees.

Finally, the investment service providers offer both banking and financial services with a focus on investment banking. They may also provide custody and administrative services in financial instruments, wealth management and other such specialized services.

While affected by the latest global economic downturn, the impact on French banks has been largely contained. This was due in part to Government's response, the comprehensive supervision and proactive regulation and also to the sound business practices of the banks themselves that focus on risk diversification.

3.2.3 Italy

One of the founding members of the European Union, Italy is part of both the Eurozone and the Schengen area[5].

During the 1990's, the Italian banking sector went through a process of structural changes marked by numerous mergers, takeovers (561 according to Heffernan, 2005) and privatization[6] that led to a decline in the number of banks (792 in 2004 as reported by Intesa Sanpaolo's website[7], one of the big European banking groups) and allowed the remaining players to enjoy the benefits of the economies of scale as the average size of the banks increased significantly.

The majority of Italian banks have a cooperative structure and there are two different types of them: "banche popolari" (BP, 38) and "banche di credito cooperativo" (BCC, 444). In terms of market share, they account approximatively for[8] 44 percent of loans and 31 percent of deposits in the Italian banking system. Specific to the Italian cooperative banks is the one-person-one-vote principle that some perceive as a limitation to the free circulation of capital. This has prompted the European Union to initiate infringement procedures against Italy.

[5] signed in November 1990, implemented from October 1997

[6] the state's share in the banking system went below 1 percent by 2004 and the domestic market is dominated by joint stock companies - 80 percent, see http://www.imf.org/external/pubs/ft/wp/2007/wp0726.pdf

[7] http://www.group.intesasanpaolo.com/portalIsir0/isInvestor/PDF_studi_eng/CMFocus%20Italian%20Banking%20Sector%20October2004.pdf

[8] see Gutiérrez (2008) at http://www.imf.org/external/pubs/ft/wp/2008/wp0874.pdf

Governance structure aside, the cooperative banks operate in the banking market much like any other player, in the pursuit of profits[9] and some of them are also listed on the stock market.

3.2.4 Netherlands

The Netherlands is a founding member of both the European Union (1952) and the Eurozone (1999). It has a developed economy that ranks, in terms of nominal GDP, as the ninth largest in the World and it is also one of the World's major exporters (top 10). Holland has important trade connections to Germany, France, and UK, especially through its port city Rotterdam, as well as Belgium and Luxembourg - the three countries forming the Benelux economic union.

The Netherlands' open economy attracts a large volume of foreign investment and benefits from a developed and internationally oriented financial system, with Amsterdam being one of the leading financial capitals of the world. The financial system includes, in the order of importance, three key sectors: banking, pensions, and insurance. At of the end of 2010, the total value of banking assets was estimated[10] at 382 percent of GDP, followed by the pensions system with 135 percent of GDP and insurance with 69 percent of GDP.

According to the 2011 statistics of the Dutch Central Bank[11], at the end of 2010 there were 85 banks licensed to operate in the Netherlands. Besides these, there were also 35 branches of EU based banks and 5 branches of non-EU institutions active, as well as a large number (497) of EU credit institutions[12] providing cross-border services.

[9]Some differences do exist, as cooperative banks are subject to specific regulations that determine the percentage of net profits to be allocated for legal reserves. Also from a legal point of view, they have limited ownership rights and while they are part of a network structure, they can make independent decisions.

[10]IMF Country Report No. 11/206, www.imf.org/external/pubs/ft/scr/2011/cr11206.pdf, 2011

[11]De Nederlandsche Bank http://www.statistics.dnb.nl.

[12]Many of them originate in UK and France and have entered the Dutch financial market after the housing boom in the 1990s.

The foreign presence in the Dutch banking market has strengthened in the last years, especially after the restructuring of ABN AMRO and in 2010 seven out of the largest 20 banks were owned by foreigners.

The global financial crisis had a significant negative effect on the Dutch economy as well as the financial and the banking sector. Due to exposure to toxic assets, a tightening of the inter-bank funding market and a worsening in business conditions (a consequence of the economic downturn), a number of banks went bankrupt or merged(at the middle of 2012, there were 78 licensed banks), while others were forced to restructure and/or required financial help from the Government, such as the Internationale Nederlanden Groep (International Netherlands Group, ING).

The difficulties of ABN AMRO, the largest Dutch financial institution, and its take over in 2007 by a consortium of Fortis, Royal Bank of Scotland, and Santander has altered the balance of power in the Dutch financial system significantly. With a worsening in the global financial conditions, this required exceptional measures from the Netherlands government, who purchased in 2008 the Dutch banking parts from Fortis, in addition to their other, more generic, measures aimed at improving the stability of the system.

Overall, the measures adopted appear to be effective and, from 2009, the Dutch banking sector has returned to profitability. Also the capitalization of all large banks is adequate and well above the legal minimum requirements. Nevertheless, there are still challenges for the banking sector and potential vulnerabilities, stemming especially from the relatively high level of indebtedness in the housing market and the banks' cross-border operations that expose the domestic system to the various current negative economic developments in Europe.

3.2.5 Scandinavia

Denmark

Denmark is a member state of the European Union since 1973, but it does not participate to the Eurozone. The country, like the UK, is not under a legal obligation to adopt the Euro, as it benefits from an opt-out in this sense, awarded in 1992. Nevertheless, for international trade purposes[13], the domestic currency is tied to the Euro, through the European exchange rate mechanism. An attempt has been made by the Danish government in 2000 to adopt the euro, but the proposal failed in a referendum vote.

According to the National Bank of Denmark[14], in May 2012 there were 107 credit institutions active in the Danish banking sector, including commercial banks, savings banks and cooperative banks. The number of banks has been decreasing steadily since 1980, when there were approximately 300 institutions, typically through mergers and acquisitions. In the last few years the trend has accelerated[15]. As a result of the financial crisis which affected the balance sheet quality of several banks.

As a result of these structural changes the banking sector in Denmark is highly concentrated. At the end of 2011, the large banks accounted for approximately 85 percent of all credit operations, with the rest being split in roughly equal parts between the medium size and the small banks. Among the large institutions, banking groups such as the Danske Bank group and Nordea Bank Danmark together were responsible for almost half of all bank lending in Denmark. Overall, a large proportion of the lending done by the Danish banks is to non-resident customers, especially in other Nordic countries, the UK and Ireland.

The Danish banking system appears not to have fully recovered from the effects of the global recession. Bank earnings continued to be low in 2011, and in many cases had stagnated or even decreased relative to 2010. Typically only the largest banks have seen an increase

[13]Many of Denmark's major trade partners are Euro users, like Germany, Netherlands, or France.

[14]National Bank of Denmark, www.nationalbanken.dk, 2012.

[15]The group of medium sized banks appears to be affected the most, so the system is evolving towards a structure with a few large banks and many small ones.

in profits with the size of their operations and product diversification. This put them in a better position to deal with the higher funding costs and reduction in lending volume faced by the smaller banks. Overall, in the recent years banks have focused on managing risks by reducing the level of their exposure and improving capital adequacy.

Sweden

Sweden joined the European Union in 1995, but decided, in 1997, not to become a member of the Eurozone. This decision was reaffirmed in a referendum in 2003. From a legal point of view, under the Maastricht Treaty, the country is obliged to eventually adopt the Euro. Nevertheless this requires the candidate to first enter voluntarily the European Exchange Rate mechanism, which Sweden has declined to do so far, effectively gaining a de facto opt-out from the monetary union. Sweden's financial system is among the most developed in Europe and is a mix of the market-based Anglo-Saxon system and the bank-based Continental European system. It consists of three types financial intermediaries: credit institutions (mainly commercial banks), investors (such as pension funds or insurance companies) and security companies

According to the National Bank of Sweden[16] at the end of 2011, there were 115 banks (4 more than in 2010) operating in Sweden, out of which 37 were limited liability (one was the subsidiary of a foreign bank), 27 foreign-owned branches, 49 savings banks (that typically have a regional presence) and two co-operative banks.

Swedish banks, especially those that are part of large financial groups, follow the concept of universal banks and fulfill a wide variety of operations.

[16]Riksbank, www.riksbank.se, 2012

In general, the level of government ownership in the banking sector is quite low, with a sizable[17] participation in Nordea (the largest bank in the system).

In terms of assets, banks are the largest among all credit institutions. At the end of 2011, total banking assets represented approximately 174 percent of GDP. The Swedish banking market is highly concentrated[18] with the country's four largest banks groups: Skandinaviska Enskilda Banken (SEB), Svenska Handelsbanken (SHB), Swedbank and Nordea accounting for 75 per cent of the total banking assets and for almost half of the credit institutions' total lending.

Regarding the banks' crediting activities, most of their loans are extended to the domestic and foreign public. At the end of 2011, the total value of bank lending in Sweden was approximately 2,501 billion SEK, or 41 percent of their total assets. Roughly 45 percent of these loans were taken by Swedish non-financial companies, 34 percent by Swedish households, 7 percent by the Swedish public sector, and 14 percent by the public abroad.

Starting in the early 2000s, the funding methods of the Swedish banks' have changed, as bank lending has increased at a faster pace than deposits, making banks increasingly dependent on financial markets. These funds are not only less stable in terms of availability than more traditional sources, but also tend to incur a higher intermediation cost, with potential negative implications on the future bank performance.

Another risk factor stems from the increased internationalization of the banks' activity, which makes the system increasingly vulnerable to regional (negative changes in the Baltic economies) or global developments, like the financial crisis at the end of the previous decade.

For the Swedish banking sector, the impact of the crisis was fairly significant.

[17] Overall, approximately 25 percent

[18] Initially bank legislation was quite restrictive in Sweden and large financial group were used as way to circumvent this impediment. At the European level, the degree of concentration is only comparable to countries like Belgium or Finland.

It created difficulties in the funding markets, particularly the euro and dollar liquidity, raised concerns about the quality of assets and brought a decline in the price of bank shares. Nevertheless, the strong rebound of the domestic economy has helped alleviate many of the negative effects, but the risk factors are still present. Overall the banking sector has proved quite resilient to credit risk.

3.2.6 Switzerland

Switzerland is a developed Western European country, with a high level of income per capita that is not a member of European Union. Nevertheless, it is still very closely tied to the EU, through trade and financial links, regulated by a series of bilateral agreements. The country's legal framework is on par with the European norms in most economic aspects[19].

The Swiss economy is dominated by the service sector with the financial segment playing a key role in this respect. According to the Swiss Bankers Association (SBA)[20] the total value added in 2011 by the financial sector to GDP was approximately 10.3 percent.

Switzerland's historical neutrality, coupled with the stability and performance of its economy make the country a very attractive choice for foreign investors. Being able to attract money cheaper than other countries is likely to have an impact on their cost structure. Also, it is estimated[21] that close to one third of the World's off-shore funds are managed by its well developed and diverse banking system, which is based on the concept of universal banking. Swiss banks are mandated to perform, in addition to the usual basic deposit and lending activities, asset and investment management, payment services, financial analysis and underwriting operations.

[19] A notable exception is agriculture where Switzerland has in place a series of protectionist measures.
[20] Swiss Bankers Association, http://www.swissbanking.org/en, 2012.
[21] according to the Boston Consulting Group.

According to the Swiss National Bank[22] at the end of 2011 there were 312 banks in Switzerland, a decline from the 327 recorded in 2008. These banks fall into one of the seven broad categories identified by the SBA: large banks, cantonal banks, private banks, regional and saving banks, Raiffeisen banks, foreign banks and other specialized types of banks.

The large banks offer all types of banking services, with a particular focus on investment banking (capital market transactions, securities trading and financial engineering) and international operations. There are two banks included in this group UBS AG and Credit Suisse Group, that together account for more than 50 percent of all banking assets in the system. Each of them has an extensive branch network, both at home and abroad - especially in the Americas and Europe.

The cantonal banks have a special statute and function under cantonal law, with the canton typically holding a minimum of one-third of the bank's capital and voting rights (this requirement was relaxed in October 1999). At the end of 2009 there were 24 cantonal banks with assets ranging from 2 billion CHF to 120 billion CHF. The smaller cantonal banks tend to focus on savings and mortgages, while the larger ones are more diversified and offer the entire spectrum of banking services. Private banks are individual enterprises[23] that focus almost exclusively on asset management with very little interest-income business. In fact, these banks are exempt from the requirement to publish annual financial statements, if they do not accept deposits from the public. Many private banks have a long tradition, in some cases dating back to the 18^{th} century, and thus they are among the oldest credit institutions in the country. As of 2010, according to the SBA's Compendium, there were 14 such institutions in Switzerland.

The regional and savings banks operate mainly in the savings and mortgage segments of the market, and are similar, in this aspect, to the small cantonal banks.

[22]Swiss National Bank, www.snb.ch/ext/stats/bankench/pdf/deen/E_Analysetext.pdf, 2012
[23]The owners have unlimited private liability terms of their personal assets.

The main difference is that they put a much greater emphasis on developing close and durable relations with their customers and, thus, they restrict their activities to a particular region in order to be as familiar as possible with local economic and business conditions. At the end of 2010, there were the 75 regional and savings banks, with the majority, 41, being members of the RBA Holding group.

Raiffeisen banks are organized as co-operatives and, at the middle of 2011, there were 328 such banks forming the Raiffeisen Group. These banks operate both regionally and at the national level, as part of their nationwide group. They conduct, besides the traditional interest business, mortgage, savings and investments activities. They also have a presence in the pension and insurance market through cooperation with the Helvetia Group.

The foreign banks are present in Switzerland either as independent credit institutions (approximately 120 in 2009) which typically provide asset management, fund management and distribution services, or as subsidiaries of their parent bank - very often based in other European countries. There were almost 30 such entities in Switzerland in 2009, engaged mainly capital market transactions.

Finally, in the generic category other banks are included very specialized institutions that offer services in areas such as consumer financing, personal loans, asset management, stock exchange, and securities trade. Usually these companies are set up as public limited firms, under private law, and are managed in Switzerland.

Regarding the business models employed by the Swiss banks, it is generally true that the large players subscribe to the integrated business approach, compatible with the universal banking philosophy adopted by these credit institutions. The small banks often use a niche strategy, where non-core business activities are outsourced, while the medium size banks fall somewhere in between.

3.2.7 United Kingdom

The United Kingdom is one of the world's most globalized economies, with large flows of foreign direct investment, in and out of the country. It sits at the center of the global financial system, with London being the world's largest financial center. In terms of nominal GDP, the UK is Europe's third largest economy (after Germany and France) and the seventh-largest in the world.

UK is a member of the European Union since 1973, but like Denmark, it has chosen not to join the Eurozone and it has obtained a special opt-out on this, so that the country is legally exempt from the requirement to adopt the Euro. However, it may do so at a later time, through a vote of the British Parliament or a referendum.

The banking sector plays a key role in the British financial system. Providing three fundamental services: payments, intermediation and risk insurance, the British bank system exhibits a high degree of concentration, especially in retail banking. The market is dominated by five large banking groups: RBS, Barclays, HSBC, Lloyds Banking Group (LBG), and Santander, as well as a mutual financial institution, Nationwide Building Society which, together, account for almost 80 percent of all lending and deposit operations. As of 2010, according to the Bank of England, there were approximately 300 banks and building societies authorized to accept deposits in the country.

These large financial groups operate as universal banks and they offer a complex and varied selection of services, ranging from securities underwriting and trading, to fund management, and general insurance. They also play an important role in the global financial market, where institutions like Barclays, HSBC and RBS hold top ten positions in market segments such as corporate and international bonds, foreign exchange and interest rate swaps.

In terms of assets, there has been a significant increase in overall banks' balance sheets in the past two decades. Cumulated in 2010, bank assets were more than five times larger than the country's annual GDP. Like in the case of market shares, a high degree of concentration can be observed in this area as well - three of the top four largest banks hold more than 60 percent of total assets. The UK banking system is comparable, based on its size relative to the economy, to Switzerland and the US.

The ongoing consolidation in the British banking sector and the expansion and diversification of banks' activities appears to be consistent with the pursuit of economies of scale. The financial deregulation the system experienced in the 1970s and 1980s, coupled with technological advances, financial innovation and the globalization of markets can all be seen as contributing factors to this behavior. Still the evidence in the literature on the matter is mixed and inconclusive.

The British banking sector was affected by the global recession triggered by the financial crisis, as the UK economy entered a recession in the second half of 2008 until the end of 2009. The drop in loan activity, as businesses slowed down, was further complicated by an increase in costs due to provisions, risk management and exposure to toxic assets. In early 2012 UK has experienced a double-dip recession which raised new questions about structural weakness in the British economy and a potential vulnerability of its financial system.

3.2.8 Emerging Economies

Croatia

Croatia is a former communist country that was part of the Republic of Yugoslavia until 1991.[24] In the early 1990s there were only 26, state owned, banks that operated in the market.

[24] On June 25^{th} 1991, the decision to separate was taken and independence was declared on October 8^{th}.

These banks were gradually privatized, but the insolvency of the debt ridden, state-owned, enterprises had a negative influence on their balance sheet quality. In an effort to address this problem, the government issued in 1991-92 the so called "big bonds"[25] that were used by state companies to repay their obligations to the banking system at nominal value.

During the 1990s, due to a permissive legislative framework (especially in terms of minimum regulations and capital requirements), the number of banks has increased steadily,[26] reaching 60 by 1997 and then decreasing to 43 by the end of 2000 following a domestic recession (1998-1999)[27]. The downsizing of the Croatian banking system was a result, in part, of international developments (the Kosovo war), but domestic factors like an insufficient capital base, irresponsible management, corruption, cost inefficiency and inadequate credit risk monitoring also played a major role.

According to the Croatian National bank[28], as of January 2011, there were 32 licensed banks in Croatia, most of these being foreign owned. The dependency of the banking sector on external financing could make it vulnerable to risks originating in the EU (especially given the recent economic developments in the area), despite the fact it had weathered the financial crisis of 2008 quite well.

On December 9^{th} 2011, Croatia signed the Treaty of Accession to become the 28^th member of the European Union. By the end of June 2013, the ratification process is expected to be finalized, so in July 1^{st} 2013 Croatia would become a full member of the Union.

[25] indexed at the producer price index and with a 20 years maturity period.

[26] It still had a high level of concentration as in 1995, the four largest banks accounted for almost 70 percent of the total assets in banking system.

[27] Together with a sharp decrease in external balances, this also lead to a tightening of fiscal and monetary policies and the government's decision to sell the remaining state-owned banks. According to a study done by the Austrian National Bank, by the end of 2004, the privately owned banks were accounting for around 97 percent of the total assets and 91 percent of shares in the overall Croatian banking system.

[28] http://www.hnb.hr/

The ascension process to the European Union created strong incentives for a better management of the Croatian financial system and performance improvements. Nevertheless, strong regulation and supervision have to be maintained in order to avoid the risk of a systemic failure, especially if the parent-companies of the Croatian banks (most of them Italian and Austrian) are affected by the sovereign debt crisis, thus limiting access to credit and raising interest rates.

Poland

Poland is a developing economy, ranked as the six largest in the EU and with one of highest, sustained, rates of growth in Europe. The country's economy continued to grow even during the latest global recession, albeit at a slower pace. The transition process from a socialist planned economy to a market-oriented system has been accomplished in a relatively short time interval in Poland, compared to many other former socialist countries, thanks to an aggressive program of reforms implemented between 1992 and 1997.

Poland was therefore able to join the European Union in the first expansion wave in May 2004, but the country is not yet part of the Eurozone. While there is no official deadline set for adopting the Euro in Poland, the authorities suggested their intention to meet the required criteria by the end of 2015, implying that Euro could potentially be introduced in 2017.

Some of the key reforms adopted in the mid-1990s have targeted the financial system, in general, and the banking system in particular. The Polish government has privatized a number of banks, improved the level of capitalization overall, and also overhauled the legal framework with the net effect of making the Polish banking system more competitive and attractive to foreign investors.

Currently, Poland has the largest and most developed financial system and banking sector in Central and Eastern Europe. According to the National Bank of Poland, the banking system comprised of 51 banks, 18 branches of foreign banks, a network of 578 cooperative banks and 1800 small credit unions, in 2009. In terms of ownership, the foreign owners controlled 37 commercial banks, which accounted for more than 70 percent of total banking assets.

Between 1997 and 2006, a series of structural changes happened in the Polish banking system. On the one hand, there was an accelerated process of mergers and acquisitions, initiated by the early privatizations and driven by technological development that resulted in increased concentration. On the other hand, during this entire period the state's participation in the system has been dramatically reduced in favor of foreign ownership, which increased from 15 percent in 1997 to more than 66 percent at the end of 2006.

In terms of financial performance, the baking sector has steadily improved during the period considered. The profitability of assets and equity has increased, while the average net interest margin has dropped from 5.4 percent in 1997 to approximately 3.2 percent in 2006. This may indicate that a higher concentration has enabled banks to achieve economies of scale, while the integration in the EU and the reduction in entry requirements for foreign banks, lead to increased competition and shifted the banks' focus to improving efficiency.

The Polish banking system appears to have been largely insulated from the effects of the global financial crisis. While the commercial banks initially reacted in 2009 by moderating their lending activities, increasing interest rates and improving capital adequacy overall, the fact that the economy continued to grow and the limited exposure of Polish banks to foreign assets have allowed the system to resume growth in the later years.

Romania

Romania is one of the two newest members (the other one being Bulgaria) of the European Union, joining the rest of the twenty five member countries in 2007. As a former communist country with a developing economy, the transition process to a market oriented economy has been quite prolonged and it has affected the country's European agenda.

Romania applied for membership to the European Union in 1993, became an Associate State in 1995, with the intention to join the Union in 2004. Nevertheless, it was not able to meet the required economic criteria at that time, becoming an Acceding Country instead, and its admittance was delayed by three years until 2007. Romania is not yet part of the Eurozone, but it intends to join before 2015.

Overall, the Romanian Financial System can be characterized as being still in a development stage, especially when compared to some of its advanced European counterparts (Germany, France). The foundation of the system was set in the early and mid-1990's through a series of reforms that ensured the transition from the former centralized framework.

The Romanian banking system plays a prominent role in the financial mechanism. It was introduced in December 1990 and is designed as a two-tier system, consisting of the National Bank of Romania and commercial banks.

According to the Annual Report, published by the National Bank of Romania, at the end of 2011 there were 41 credit institutions operating in Romania. The data suggest that the Romanian banking market is quite attractive to foreign capital, with 26 commercial banks that have a majority of foreign-owned capital and 8 branches of foreign banks versus only 4 private banks with a majority of domestic owned capital and 2 banks with either fully or a majority of state-owned capital. There is also a domestic cooperative bank network active.

The Romanian banking system is highly concentrated. The top five banks account for 54.6 percent of total banking assets.

Also, in terms of market shares, the foreign banks dominate by far with 83 percent of total assets, followed by credit institutions with a majority of Romanian private-owned capital at 8.8 percent and then the state-controlled banks with 8.2 percent. Romania experienced a significant economic downturn in 2009 and 2010 in the wake of the global financial crisis. This translated into a considerable drop in lending activity, as banks became more concerned about managing risks and the demand for credit from the economy declined. At the same time the volume of provisions constituted by banks has increased, which negatively affected their costs. In terms of capitalization, the banking system has maintained overall high levels of capital adequacy and, at the end of 2011, the solvency ratio was 14.87

Serbia

Serbia, like Croatia, was part of the former Republic of Yugoslavia, but it did not choose to break away in the early 1990s. Together with Montenegro, it formed, until 2003, the Federal Republic of Yugoslavia and, later, until 2006, Serbia and Montenegro. In 2006 Montenegro chose, by referendum, to end their union and Serbia became an independent state. In December 2009, Serbia applied for admittance to the European Union and, in March 2012, was recognized as an official candidate.

At the end of the first quarter of 2010, according to the National Bank of Serbia[29] there were 34 commercial banks operating in the country, with a combined labor force of over 31,000 employees. Most of these banks (21) were foreign owned[30] and, out of the 13 domestic banks, 8 were owned by state, while the rest were private. These are organized in a national banking network that included over 2,600 business units, branches, branch offices and teller units in 2010, in a slight decline from the previous year.

[29] National Bank of Serbia, www.nbs.rs/export/sites/default/internet/english/55/55_4/quarter_report_I_10.pdf.

[30] The foreign banks are members of banking groups from 11 countries.

The value of the banking sector assets in 2010 was estimated at RSD 2,237 billion, while capital totaled RSD 470 billion. The foreign banks accounted for the majority of assets and capital in the sector, while the domestic banks (state and private combined) held only 26 percent of total assets and 28 percent of both capital and banking sector employment. Profits were split more evenly between the two groups, with a 47 percent share for the domestic banks.

Overall the Serbian banking sector appears quite fragmented, with only modest concentration in the various market segments[31], thus showing great potential for future growth and development.

The effects of the latest global recession on the country's banking system were moderate, with relatively small declines in activity and employment during 2009 and in the first part of 2010. Nevertheless, the structure of foreign ownership in the sector, with a large share of banking assets originating in countries[32] like Italy (21 percent) and Greece (16 percent), is potentially worrying, especially if the European sovereign debt crisis deepens in the near future.

Slovenia

Slovenia became a member of the European Union in 2004 and, starting with 2007, it has adopted the Euro as its national currency. According to its central bank (http://www.bsi.si/en/) at the end of 2011 there were 19 banks active in the Slovenian market, which included eight subsidiary banks, three branches of foreign banks and three savings banks. Out of the 19 banks that formed the Slovenian banking system, 11 were under domestic ownership (with three being totally domestic) and eight banks were under majority foreign ownership.

[31] The Herfindahl Hirschman Index of concentration has values well below moderate concentration (1000), for all categories: lending, deposits, income, etc.

[32] Other important countries are Austria with 21 percent and France at 7 percent.

The domestic banks also held the larger market share, 71 percent versus 28.9 percent, for the foreign banks in 2007.

The fraction of the banks' equity held by foreigners was approximately 39 percent in 2011. In terms of assets commercial banks have the highest share, roughly 70 percent of the system's total assets (EUR 48.8 billion at the end of 2011). Over the course of 2010 there has been a 3.1 percent decline in bank assets, reflecting a reduction of debt towards the rest of the world that was largely offset through funding from the Eurosystem.

The majority of the employees in the banking sector are women (74.1 percent) and the personnel of the largest bank (Nova Ljubljanska banka) represent nearly 30 percent of all employees in the banking sector. There is a preference for internal recruiting practices and emphasis is placed on education and training.

The recent crisis affected the performance of the banking sector, mainly through a decline in deposit and lending activities, as well as a worsening in the value and liquidity of eligible collateral. The banks responded to the situation by reducing investments in securities, the volume of loans to non-banking sector and increased attention to risk management.

A worsening European debt crisis coupled with a decline in economic growth in Slovenia and its trading partners and the country's dependency on foreign financing could have important negative consequences on the banking system's capacity to access low interest rates loans and overall cost level.

Turkey

Turkey is an associate member of the European Union and has been an official candidate for full membership since December 1999. Negotiations between Turkey and the EU have been ongoing since 2005 and it is expected that the country will not be able to join before 2015.

Turkey is typically considered to be a newly industrialized country or, in some sources like the World Bank, an emerging market. It has a large economy (ranked in the top 17, by nominal GDP) that has been growing at a fast pace for the past decade. Key industries such as steel, energy, ship-building, telecommunications and financial services are all well represented in the Turkish economy. The country also enjoys close financial and trade links with the EU and is a member of EU Customs Union since 1995.

Before 1991, the regulations to establish private banks in Turkey were overly restrictive which kept the number of deposit institutions low. A relaxation of the Government's control on the sector, in the early 1990s has led to a rapid increase in the number of banks. The number reached 72 banks in 1998 and this increase was combined with a steady decline in the balance sheet quality of many of these institutions.

The situation culminated in a financial crisis in 2001 that led to a profound restructuring of the entire system. In the wake of this crisis, a wave of bank mergers and acquisitions followed. This consolidated and sanitized the banking sector, reducing the number of active banks to only 31 and inducing a significant increase in performance in the 2002-2008 period. During this time, the value of bank assets increased from 57 percent of GDP to more than 80 percent, as well as the number of personnel and branches.

The current Turkish banking sector is considered to be one of the most developed and secure in Eastern Europe and Middle East. It is the major component in Turkey's financial system and plays a key role in supporting its booming economy.

According to the National Bank of Turkey in 2009, there were 49 banks authorized to operate in the country. The majority, 32 of them, were commercial banks, while 13 were development and investment banks and the remaining 4 participation banks. The development and investment banks are forbidden, to issue deposit and participation certificates.

Overall, the value of all banking assets, at the end of 2008, was equivalent to 88 percent of GDP. The majority of these assets were concentrated with the commercial and investment banks - roughly 96 percent. In terms of ownership, the private commercial banks accounted for 49 percent of all assets, while state banks represented 30 percent and foreign banks only 14 percent.

The effect of the global recession of 2008-2009, on the Turkish banking sector was more limited than in many other European countries. After the 2001 domestic crisis, the system had been strengthened considerably in terms of capital adequacy ratio, asset quality, risk management (currency, liquidity, interest and maturity) as well as supervision, and all these factors played an important role in insuring its resilience. Nevertheless, the increase in the cost of external borrowing and currency liquidity had a moderate negative effect on bank lending activities.

Chapter 4
Data Description

This study utilizes banks' balance sheet and income statement data for 14 European national banking markets from 2001 until 2009. The data was obtained from the BankScope Database (Bureau van Dijk Electronic Publishing) and refers to commercial, savings and cooperative banks only[1]. The selected sample includes banks with at least $100 million in total assets and after filtering out all missing, zero and unusual[2] observations, consists of an unbalanced panel with 13,970 observations. All monetary variables are expressed in millions of U.S. dollars, adjusted for inflation (constant 2009 dollars).

The selected countries, namely Croatia, Denmark, France, Germany, Italy, Netherlands, Poland, Romania, Serbia, Slovenia, Sweden, Switzerland, Turkey, and United Kingdom, were picked in order to offer a picture as comprehensive as possible of the European banking market in terms of legislation (EU members and non-EU countries), size of the economy and of their national banking sector.

More specifically, France, Germany, Italy, Netherlands, Slovenia are members of the European Union and are also part of the Eurozone. Sweden, Romania, Poland, Denmark, UK are European Union members as well, but are not yet part of Eurozone.

[1] We have left out other types of banks such as real estate and mortgage banks, medium and long term credit banks and investment banks since the operations of these specialized institutions can be, in many cases, quite different from those of an archetypal (commercial) bank that we consider here.

[2] Negative values for equity or negative total operating expenses may suggest inaccuracies in the data entry.

Switzerland (neutral) is not part of either, while Turkey, Croatia and Serbia are EU candidates. The corresponding ISO Alpha-2 country codes are given in Table 4.1.

Table 4.1: ISO Alpha-2 Country Codes

Country	ISO Alpha-2 code
CROATIA	HR
DENMARK	DK
FRANCE	FR
GERMANY	DE
ITALY	IT
NETHERLANDS	NL
POLAND	PL
ROMANIA	RO
SERBIA	RS
SLOVENIA	SI
SWEDEN	SE
SWITZERLAND	CH
TURKEY	TR
UNITED KINGDOM	UK

In the sample, Germany has the highest number of bank year observations, 8,668, followed by Italy with 1,818 and Switzerland with 1,188. Among the other countries, developed economies from Western Europe are typically the best represented with a number of observations ranging from 527 for France to 344 for Sweden. An exception is the Netherlands with only 134 bank year observations, which is comparable to developing European countries such as Croatia (121), Romania (104) and Poland (93). At the low end of the spectrum there are countries like Slovenia, Turkey and Serbia with around 80 bank year observations each.

In the banking literature, there is not a widespread consensus regarding the definition of bank inputs and outputs, which largely depends on the particular role attributed by the researcher to the bank. In defining these variables, the present study follows one of the more commonly used methods, the so-called intermediation approach (Sealey and Lindley 1977), which primarily views the bank as an intermediary between its depositors and borrowers using deposits together with purchased inputs to produce various categories of bank assets (loans and securities), measured by their dollar values.

To calculate the stochastic cost frontier, we consider two bank input prices represented by the interest rate paid on deposit funds (avrate) calculated as the ratio between interest expenses and total deposits, and the average wage of employees (avwage) given by personnel expenses divided by the number of employees. Also, there are two bank outputs given by total loans extended by the bank and total securities held. Finally, we also need total costs which are defined as the sum of interest expenses and total operating expenses.

In order to ensure that the cost frontier is homogeneous of degree one, we use the average interest rate paid on deposits funds (avrate) as a normalizing factor. To control for banks' exposure to risk, the outputs and cost are normalized by total equity. To summarize the variables, we include the box and whiskers diagrams for the normalized loans (Figure 4.1), normalized securities (Figure 4.2) and normalized average wage (Figure 4.3).

Table 4.2 presents succinctly the definitions of the output, price, cost and other variables used in our analysis, while tables 4.3, 4.4, 4.5 and 4.6 contain the summary statistics for each of the 14 countries, as well as for the pooled sample.

The summary information suggests, at a glance, that there is a potentially significant degree of heterogeneity between the various European banking markets. For instance, in terms of equity volume, it appears that the banks with the highest equity level are concentrated in the UK (3,387.06 million USD), Netherlands (2,850.34 million USD), France (2,362.64 million USD) followed by Turkey (1,713.08 million USD) and Poland (870.27 million USD). The average level of bank equity for these five countries is almost five times larger than the sample average (457.65 million USD).

At the same time, Germany and Eastern and Central European countries like Serbia, Croatia, Slovenia and Romania seem to be dominated by banks with relatively small equity level which is roughly one third to two thirds of what we observe for the overall sample.

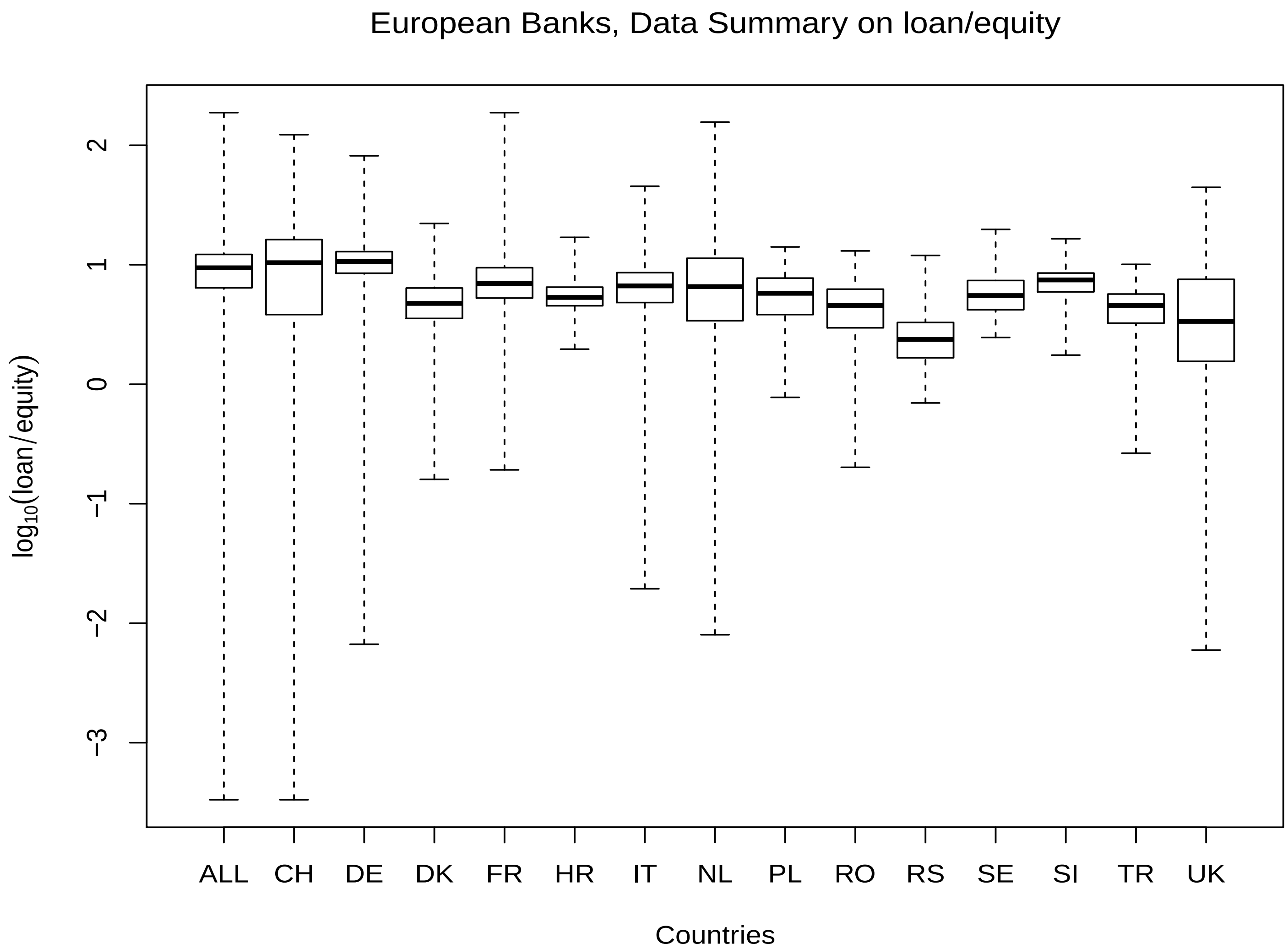


Figure 4.1: Box and Whiskers Diagram for loan/equity.

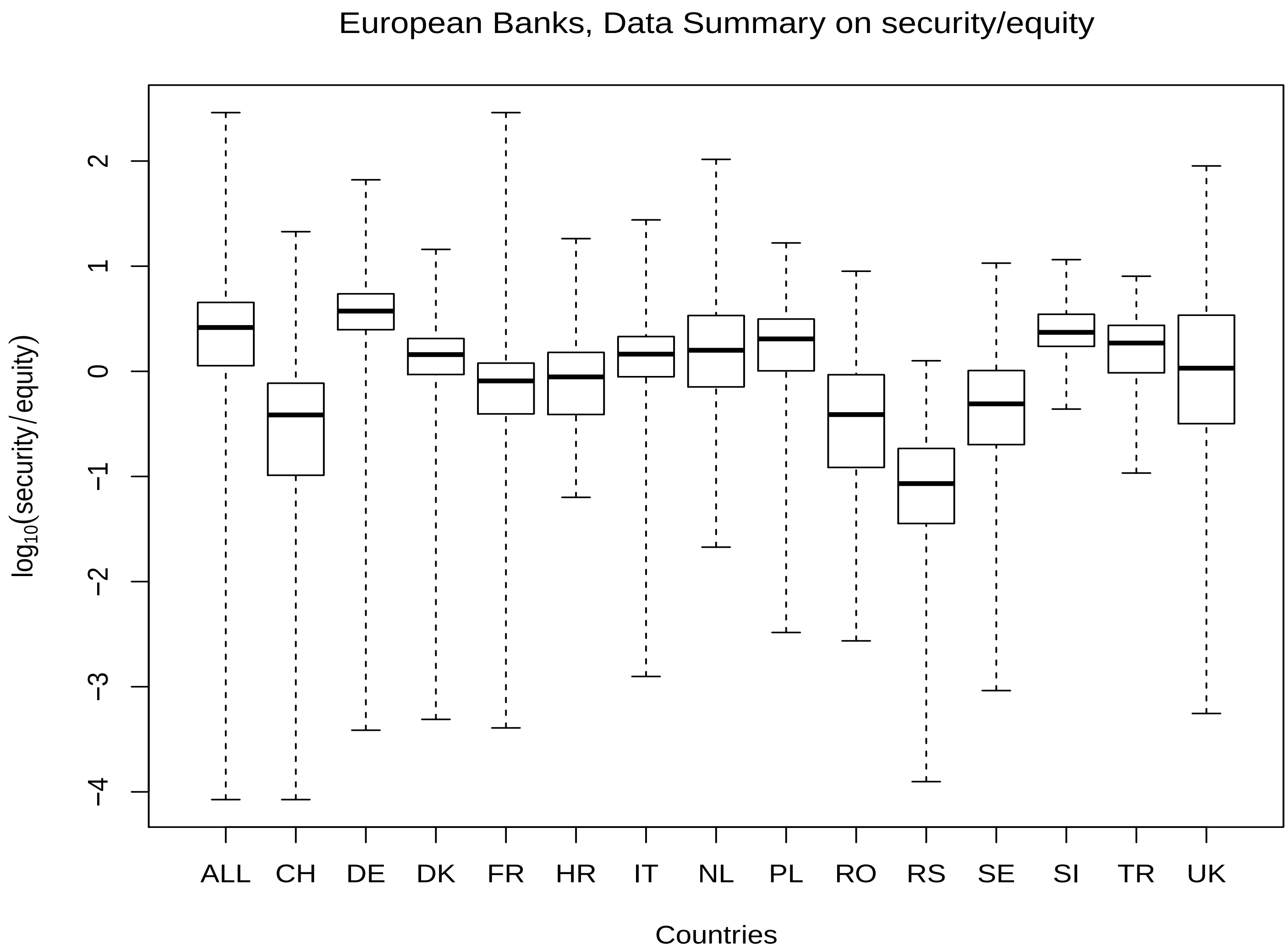


Figure 4.2: Box and Whiskers Diagram for security/equity.

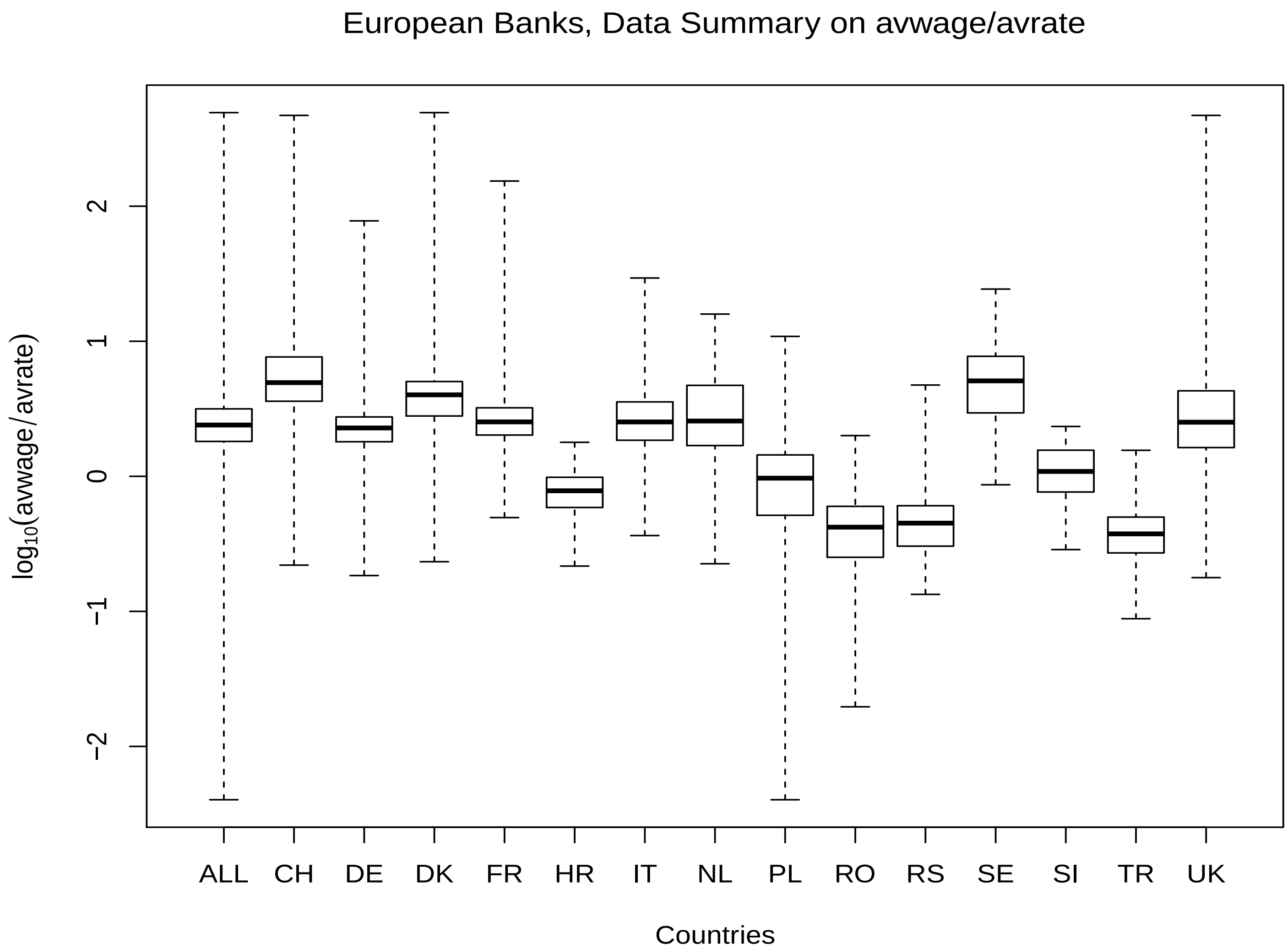


Figure 4.3: Box and Whiskers Diagram for avwage/avrate.

Table 4.2: Variable Definitions

Variable	Description
Cost	Total cost representing operating and interest expenses
Loans	Dollar value of consumer, commercial and industrial, real estate and other outstanding credits
Total securities	Investments aggregate securities, equity investment and other investment
Wage	Salaries and employee benefits divided by the number of full-time employees
Rate	Interest paid on transfers, savings, and retail time deposits divided by the total dollar value of these deposits
Equity	Dollar value of equity capital
Total deposits	The dollar value of transaction, savings, and retail time deposits.
Profit before tax	Profit before corporate income tax
Net income	Net income from the bank's income statement
Total assets	Dollar value of balance sheet total assets
Interest expense	Dollar value of interest paid on transaction, savings, and retail time deposits
Personnel expenses	Salaries and employee benefits
Total operating expense	Dollar value of expenses resulting from the bank's normal business operations
Number of of employees	Number of full time employees

Conversely, Sweden and Switzerland are close to the sample average with 440.12 and 431.1 million USD, respectively, while in Italy the average bank equity is roughly one and a half times larger than that (611.11 million USD).

The data about the average number of bank employees corroborates with the information regarding the national bank equity level. Again the average number of full time bank employees in Poland (7,613.33), United Kingdom (6,437.62), Turkey (4,998.49), Netherlands (4,200.67) and France (3,597.76) is significantly above the sample average of 931.78. The other countries, with the exception of Romania (2,826.29), are much closer to the pooled sample average, with some countries like Italy (1,077.40) and Serbia (993.59) being a bit above, while the rest are at or below the average.

Table 4.3: Summary Statistics of Variables by Country

Variable*	FULL SAMPLE	HR	DK	FR	DE
Cost	413.9	93.2	297.41	2097.83	173.11
(s.d.)	(3551.95)	(139.87)	(1267.63)	(9087.73)	(1893.58)
Loans	4479.64	904.49	5032.29	18987.22	1652.2
(s.d.)	(35798.84)	(1342.55)	(23432.34)	(72371.98)	(11821.19)
Total securities	3460.45	208.43	1108.01	21391.77	1391.42
(s.d.)	(47578.41)	(359.43)	(5327.17)	(128661.1)	(30514.22)
Wage†	76847.3	26805	94450.5	104348.7	66096.8
(s.d.)	(50131.5)	(8455)	(37375.2)	(99578.2)	(38188)
Rate	3.2%	3.62%	2.92%	3.91%	2.97%
(s.d.)	(1.98%)	(1.16%)	(3.7%)	(2.41%)	(0.87%)
Equity	457.65	162.14	380.6	2362.64	156.1
(s.d.)	(3509.76)	(245.88)	(1300.21)	(8793.16)	(1218.89)
Total deposits	5606.97	1141.26	3450.07	25372.13	2417.81
(s.d.)	(45473.68)	(1666.21)	(14912.78)	(102081.4)	(18181.9)
Profit before tax	63.3	21.62	51.28	256.61	16.06
(s.d.)	(562.01)	(38.27)	(194.05)	(1041.83)	(212.98)
Net income	48.66	17.47	38.64	197.58	11.87
(s.d.)	(447.45)	(30.75)	(142.26)	(799.38)	(194.93)
Total assets	10106.11	1588.92	7418.75	52972.01	3747.51
(s.d.)	(97279.52)	(2345.18)	(33812.37)	(260246.2)	(45984.24)
Interest expenses	244.61	41.61	204.02	1331.48	105.72
(s.d.)	(2251.25)	(65.63)	(985.02)	(5944.98)	(1352.2)
Personnel expenses	80.46	19.08	45.99	374.09	31.18
(s.d.)	(710.1)	(27.98)	(150.81)	(1576.37)	(304.32)
Total operating expenses	169.29	51.59	93.39	766.35	67.39
(s.d.)	(1396.04)	(77.15)	(314.97)	(3342.17)	(547.47)
No. of employees	931.78	736.6	458.15	3597.76	407.5
(s.d.)	(6452.56)	(1137.6)	(1438.68)	(14041.94)	(1944.91)
Obs.	13970	121	375	527	8668

Notes: All financial variables are measured in millions of constant 2009 dollars, unless otherwise indicated.
* Given at their respective sample mean.
† Measured in 2009 dollars.

Table 4.4: Summary Statistics of Variables by Country

Variable*	FULL SAMPLE	IT	NL	PL
Cost	413.9	394.71	2871.29	527.11
(s.d.)	(3551.95)	(3453.12)	(9199.18)	(693.5)
Loans	4479.64	5400.03	39684.24	5137.71
(s.d.)	(35798.84)	(43410.15)	(125934.5)	(7670.35)
Total securities	3460.45	1747.39	16010.28	2254.73
(s.d.)	(47578.41)	(19454.2)	(65317.29)	(2907.98)
Wage†	76847.3	91408.2	115426.4	43784.2
(s.d.)	(50131.5)	(20795.4)	(50556)	(46735.5)
Rate	3.2%	3.85%	5.7%	4.65%
(s.d.)	(1.98%)	(1.94%)	(6.41%)	(4.27%)
Equity	457.65	611.11	2850.34	870.27
(s.d.)	(3509.76)	(4761.41)	(9261.18)	(1309.27)
Total deposits	5606.97	4854.32	37971.74	7220.65
(s.d.)	(45473.68)	(38767.69)	(130146.2)	(9723.3)
Profit before tax	63.3	70.98	332.25	168.76
(s.d.)	(562.01)	(494.07)	(1052.53)	(290.65)
Net income	48.66	50.97	279.91	147.28
(s.d.)	(447.45)	(384.6)	(896.85)	(243.57)
Total assets	10106.11	8824.29	65307.07	9071.91
(s.d.)	(97279.52)	(74830.83)	(213001.2)	(11864.94)
Interest expenses	244.61	194.19	1983.9	215.45
(s.d.)	(2251.25)	(1900.06)	(6475.94)	(262.01)
Personnel expenses	80.46	89.03	422.62	134.65
(s.d.)	(710.1)	(696.3)	(1447.39)	(196.76)
Total operating expenses	169.29	200.52	887.39	311.65
(s.d.)	(1396.04)	(1613.71)	(2871.59)	(442.93)
No. of employees	931.78	1077.4	4200.67	7613.33
(s.d.)	(6452.56)	(9059.53)	(14129.27)	(14744.36)
Obs.	13970	1818	134	93

Notes: All financial variables are measured in millions of constant 2009 dollars, unless otherwise indicated.

* Given at their respective sample mean.

† Measured in 2009 dollars.

Table 4.5: Summary Statistics of Variables by Country

Variable*	FULL SAMPLE	RO	RS	SI
Cost	413.9	244.8	94.61	152.29
(s.d.)	(3551.95)	(305)	(72.88)	(218.1)
Loans	4479.64	1538	528.17	1718.92
(s.d.)	(35798.84)	(2206.46)	(537.23)	(2445.5)
Total securities	3460.45	183.22	23.47	607.26
(s.d.)	(47578.41)	(297.21)	(31.08)	(813.35)
Wage†	76847.3	21271.9	17291.2	43588.1
(s.d.)	(50131.5)	(9258.3)	(4928.7)	(15800.3)
Rate	3.2%	5.98%	4.44%	4.22%
(s.d.)	(1.98%)	(3.7%)	(2.56%)	(1.51%)
Equity	457.65	282.22	203.19	244.01
(s.d.)	(3509.76)	(336.77)	(174.29)	(266.32)
Total deposits	5606.97	2097.17	647.12	1937.41
(s.d.)	(45473.68)	(2619.68)	(670.87)	(2345.89)
Profit before tax	63.3	56.7	22.86	34.7
(s.d.)	(562.01)	(104.74)	(25.8)	(43.61)
Net income	48.66	47.53	21.41	26.5
(s.d.)	(447.45)	(87.93)	(23.58)	(32.81)
Total assets	10106.11	2716.66	964.44	2786.52
(s.d.)	(97279.52)	(3444.02)	(927.42)	(3890.68)
Interest expenses	244.61	116.61	28.83	78.01
(s.d.)	(2251.25)	(161.35)	(31.63)	(105.13)
Personnel expenses	80.46	51.13	16.76	32.14
(s.d.)	(710.1)	(60.36)	(14.35)	(51.92)
Total operating expenses	169.29	128.19	65.78	74.29
(s.d.)	(1396.04)	(150.55)	(52.07)	(115.81)
No. of employees	931.78	2826.39	993.59	889.25
(s.d.)	(6452.56)	(3320.4)	(823.54)	(1554.45)
Obs.	13970	104	80	84

Notes: All financial variables are measured in millions of constant 2009 dollars, unless otherwise indicated.
* Given at their respective sample mean.
† Measured in 2009 dollars.

Table 4.6: Summary Statistics of Variables by Country

Variable*	FULL SAMPLE	SE	CH	TR	UK
Cost	413.9	371.23	480.2	1522.81	2942.89
(s.d.)	(3551.95)	(1850.34)	(4788.22)	(2103.2)	(9897.94)
Loans	4479.64	6270.99	3323.01	7238.61	38811.62
(s.d.)	(35798.84)	(30067.47)	(23409.42)	(10458.68)	(135974.9)
Total securities	3460.45	2108.73	4308.13	4414.24	36427.17
(s.d.)	(47578.41)	(11852.27)	(50231.61)	(7494.8)	(168499.3)
Wage†	76847.3	83825	116126.3	39983.7	125278
(s.d.)	(50131.5)	(19856.7)	(56522.9)	(16881.4)	(124646.5)
Rate	3.2%	1.88%	2.17%	11.35%	4.7%
(s.d.)	(1.98%)	(1.11%)	(1.69%)	(4.35%)	(4.39%)
Equity	457.65	440.12	431.1	1713.08	3387.06
(s.d.)	(3509.76)	(1936.25)	(3243.25)	(2717.75)	(11233.17)
Total deposits	5606.97	4927.61	6756.76	9789.83	48590.92
(s.d.)	(45473.68)	(23785.11)	(61927.33)	(14464.46)	(165894.8)
Profit before tax	63.3	78.8	76.52	377.43	681.11
(s.d.)	(562.01)	(373.81)	(715.68)	(605.82)	(2366.75)
Net income	48.66	61.61	65.38	302.25	511.97
(s.d.)	(447.45)	(296.33)	(636.41)	(482.39)	(1774.27)
Total assets	10106.11	10384.18	11546.25	14693.03	94439.96
(s.d.)	(97279.52)	(51004.14)	(111077.2)	(21814.03)	(345911)
Interest expenses	244.61	250.48	272.9	959.24	1619.28
(s.d.)	(2251.25)	(1304.7)	(2948.71)	(1363.02)	(5581.09)
Personnel expenses	80.46	63.11	133.08	209.06	569.4
(s.d.)	(710.1)	(300.51)	(1286.68)	(281.55)	(2132.02)
Total operating expenses	169.29	120.75	207.29	563.57	1323.61
(s.d.)	(1396.04)	(575.49)	(1917.07)	(763.98)	(4636.05)
No. of employees	931.78	719.17	614.06	4998.49	6437.62
(s.d.)	(6452.56)	(3371.21)	(5331.12)	(6027.37)	(22842.99)
Obs.	13970	344	1188	84	350

Notes: All financial variables are measured in millions of constant 2009 dollars, unless otherwise indicated.
* Given at their respective sample mean.
† Measured in 2009 dollars.

Consistent with the information on average bank equity, Germany, which had the lowest equity value in the sample (approximately one third of the pooled sample average), also has the lowest (average) number of employees per bank, 407.50, less than half the sample average.

In terms of input prices, the United Kingdom, closely followed by Switzerland, and the Netherlands, have the highest average annual wages of \$125,278, \$116,126.30 and \$115,426.40, respectively which are more than one and half times larger than the sample mean of \$76,847.30. At the opposite end of the spectrum there are countries like Croatia (\$26,805), Romania (\$21,271.90) and Serbia (\$17,291.20).

One potential explanation why countries like Romania, and to a lesser extent Poland, that despite having a relatively modest level of average bank equity, are well above the sample average in terms of employees, might very well lie in the relatively low cost of labor in these countries and a tendency for overstaffing that characterizes many of the former communist countries.

Regarding the interest rates, it appears that there is more homogeneity, in the sense that the developed and developing countries, respectively, face pretty similar rates in their own group. For developed countries like Sweden, Switzerland, Denmark and Germany the average interest rate varies between 1.88 percent (the minimum) for Sweden to 2.97 percent for Germany, well below the sample average of 3.20 percent.

For the second group that includes the developing countries and a few developed countries, such as France, UK and the Netherlands, the range of values is between 3.62 percent for Croatia and 5.98 percent for Romania. A notable exception is Turkey that has an average interest rate for the period considered of 11.35 percent, three and a half times higher than the sample average, which is due to the very high inflation rates it had experienced in the early 2000's.

In terms of costs, the highest values are for the banks in UK ($2,942.89 million), the Netherlands ($2,871.29 million), France ($2,097.83 million) and Turkey ($1,522.81 million) sensibly above the sample mean of $413.90 million, while the lowest costs are registered by the Croatian and Serbian banks with $93.20 and $94.61 million respectively. German and Slovenian banks are also on the lower end of the cost spectrum with $173.11 and $152.29 million respectively, while the rest of the countries have costs much closer to the sample average, ranging from $244.80 million, for Romania, to $527.11 million for Poland.

Regarding the outputs, in terms of loans the Dutch (39,684.24 million USD) and British banks (38,811.62 million USD) register the highest average volume, almost nine times larger than the sample average (4,479.64 million USD), followed next by the French banks (18,987.22 million USD) and then the Turkish and Swedish banks with sensibly smaller figures, 7,238.61 million USD and 6,270.99 million USD, respectively. The average loan volume for other developed countries is relatively close to the full sample mean, while the developing countries, with the sole exception of Poland (5,137.71 million USD), are below the mean. The lowest value, 528.17 million USD, for Serbia, represents only 11.79 percent of the mean.

Finally, for securities the situation looks fairly similar. The United Kingdom (36,427.17 million USD), France (21,391.77 million USD) and the Netherlands (16,010.28 million USD) are still in the lead and several times above the sample average of (3,460.45 million USD). With the exception of Turkey (4,414.24 million USD) and Switzerland (4,308.13 million USD) all other countries have a volume of securities well below average. The developed countries, and again Poland (2,254.73 million USD), are between two thirds and one third of the full sample mean, while the developing economies are all below one third with the lowest value held by Serbia (only 23.47 million USD)

Corroborating the information about costs with the revenues generated, by looking at the profit before tax, it becomes apparent that yet again the leaders in terms of profitability are the British ($681.11 million), Turkish ($377.43 million), Dutch ($332.25 million), French

($256.61 million), and Polish banks ($168.76 million) that are all well above the sample average of ($63.30 million). At the lower end we have countries such as Slovenia, Serbia, Croatia and Germany with a profit before tax between ($34.70 million) and ($16.06 million) for Germany.

Chapter 5
Measuring Efficiency in the Banking Sector Using a Bayesian Single Stochastic Cost Frontier Model

5.1 Introduction

In this chapter we use a stochastic cost frontier model and a Bayesian approach to examine the inefficiency of the banking sector in various European countries by estimating individual frontiers for each country. We have selected countries that differ significantly in terms of legislation (EU members and non-EU countries), size of the economy and of the banking sector in an attempt to get a more comprehensive picture of the European market.

The chapter describes the model specification and methodology, followed by empirical results presentation and conclusions.

5.2 Model Specifications and Methodology

Beginning with the seminal contributions of Aigner, Lovell and Schmidt (1977) and Meeusen and van den Broek (1977), the field of stochastic frontier models has produced a vast number of empirical studies on firm efficiency and productivity.

In particular, there is a large literature which focuses on banking efficiency because of the insight it offers into the bank's performance. Under the assumption that higher efficiency is expected to "lead to improved financial products and services, a higher volume of funds intermediated, greater and more appropriate innovations, a generally more responsive financial system, and improved risk-taking capabilities"[1], it becomes important to understand and evaluate banks' behavior and performance.

As rational economic agents, the banks are assumed to pursue optimal behavior, minimizing cost and/or maximizing profit. In a perfectly competitive market, the two objectives: profit maximization and cost minimization are equivalent, but in imperfect competition (due to market regulation, asymmetric information, etc.), analyzing both aspects of the problem is not a redundant endeavor anymore.

This chapter focuses on measuring cost efficiency in the European banking sector relative to different, individual cost frontiers for each country. We use a Bayesian stochastic frontier approach to estimate individual cost frontiers for banks in different countries, using costs, input prices and output levels from banks operating within their own countries. The model provides a relative measure of inefficiency with respect to the benchmarked frontiers for each analyzed country.

Begin with the basic stochastic cost function model:

$$\ln(c_i) = f(p_i, q_i) + v_i + u_i, \tag{5.1}$$

where c_i is the total observed cost of bank i, with $i = 1, ..., N$, N=total number of observations (banks), while $f(p_i, q_i)$ represents the cost frontier of the efficient bank that faces a set of input prices (p_i) to produce certain levels of outputs (q_i).

[1]If "efficiency profit gains are channeled into improved capital adequacy positions" as Molyneux et al. (1997) point out.

Using this model, a bank's deviation from the cost frontier ($f(p_i, q_i)$) is explained on the one hand by the statistical noise (u_i is the symmetric error component) and on the other hand by the presence of inefficiency (v_i is the non-negative inefficiency component). A measure of the bank's inefficiency[2] is constructed as follows:

$$\mathrm{CE}_i = \frac{\exp\left[f(p_i, q_i)\right]\exp\left(u_i\right)}{c_i} = \exp\left(-v_i\right) = r_i. \tag{5.2}$$

The translog cost function with multiple inputs and outputs is used[3] to specify the cost frontier as it is the most popular functional form used in the banking literature:[4]

$$\begin{aligned} f(p,q) = \alpha_0 + \sum_{j=1}^{2}\alpha_j \ln(q_j) + \sum_{k=1}^{2}\beta_k \ln(p_k) + \frac{1}{2}\sum_{j=1}^{2}\sum_{k=1}^{2}\alpha_{jk}\ln(q_j)\ln(q_k) \\ + \frac{1}{2}\sum_{j=1}^{2}\sum_{k=1}^{2}\beta_{jk}\ln(p_j)\ln(p_k) + \sum_{j=1}^{2}\sum_{k=1}^{2}\gamma_{jk}\ln(q_j)\ln(p_k) \end{aligned} \tag{5.3}$$

where $\alpha_{jk} = \alpha_{kj}$ for all $j, k = 1, 2$, $\sum_{k=1}^{2}\beta_k = 1$, $\sum_{k=1}^{2}\beta_{jk} = 0$, and $\sum_{k=1}^{2}\gamma_{jk} = 0$.

When it comes to choosing the inputs and outputs of a bank's production function, there is a significant debate about the dual nature of deposits. As explained by Berger and Humphrey (1997)[5], on the one hand the deposits "are paid for in part by interest payments and the funds raised provide the institution with the raw material of ingestible

[2]following Kumbhakar and Lovell(2003).

[3]following Lewis and Terrell (2011)

[4]McAllister and McManus (1993), and Mitchell and Onvural (1996) found evidence that the translog functional form does not fit the data very well when there is a wide range in the data in terms of banks' output size which may be leading to differences in results on scale economies across studies. Nevertheless, Berger and Mester (1997) investigated the sources in differences between the financial institutions in terms of efficiency using data on U.S. banks over the 1990-1995 period and found that the efficiency estimates are fairly robust to differences in methodology. Choices of cost or profit approach, translog or Fourier specifications, made little difference in their empirical findings in terms of average industry efficiency or rankings of individual firms.

[5]in their efficiency studies they find that efficiency is somewhat higher when deposits are specified as an output.

funds" exhibiting traits of an input, and on the other hand, they have output characteristics since "they are associated with a substantial amount of liquidity, safekeeping, and payments services provided to depositors."

In our application, the banks are modeled as productive entities that are using labor and purchased funds to produce loans, deposits and other earning assets. The input prices in this case are the wage and the interest rates, while the outputs are loans and securities.

The price of labor (avwage) is computed as the personnel expenses per employee, while the price of funds (avrate) is calculated as a ratio between the interest rate expenses and total deposits. We normalize the total cost, loans, and securities by equity to control for bank's exposure to risk and we scale the normalized total cost and the price of labor by the price of funds in order to guarantee the linear homogeneity of the cost function.

Inserting these variables into the translog cost function leads to the formula:

$$\begin{aligned}
\ln\left(\frac{\text{cost}}{\text{equity} \times \text{avrate}}\right) &= \beta_1 + \beta_2 \times \ln\left(\frac{\text{avwage}}{\text{avrate}}\right) + \beta_3 \times \left[\ln\left(\frac{\text{avwage}}{\text{avrate}}\right)\right]^2 \\
&+ \beta_4 \times \ln\left(\frac{\text{loan}}{\text{equity}}\right) + \beta_5 \times \left[\ln\left(\frac{\text{loan}}{\text{equity}}\right)\right]^2 \\
&+ \beta_6 \times \ln\left(\frac{\text{security}}{\text{equity}}\right) + \beta_7 \times \left[\ln\left(\frac{\text{security}}{\text{equity}}\right)\right]^2 \\
&+ \beta_8 \times \left[\ln\left(\frac{\text{avwage}}{\text{avrate}}\right)\right] \times \ln\left(\frac{\text{loan}}{\text{equity}}\right) \\
&+ \beta_9 \times \left[\ln\left(\frac{\text{avwage}}{\text{avrate}}\right)\right] \times \ln\left(\frac{\text{security}}{\text{equity}}\right) \\
&+ \beta_{10} \times \left[\ln\left(\frac{\text{loan}}{\text{equity}}\right)\right] \times \left[\ln\left(\frac{\text{security}}{\text{equity}}\right)\right] \\
&= \sum_{m=1}^{10} \beta_m \mathbf{x}_{.\mathbf{m}}
\end{aligned} \tag{5.4}$$

where $\mathbf{x_{.m}} = (x_{1m}, x_{2m}, ..., x_{Nm})^T =$ is the column vector that stacks all observations for the m's translog variable.

This allows us to rewrite the model as a linear composed error model for which we assume that the inefficiency term follows an exponential distribution while the statistical noise is normally distributed:

$$\begin{cases} y_i = \mathbf{x}_{i.}\boldsymbol{\beta} + v_i + u_i \\ v_i \sim \text{EXP}(\lambda) \\ u_i \sim N(0, \sigma_u^2) \end{cases}$$

where $\mathbf{x_{i.}} = (x_{i1}, x_{i2}, ..., x_{iM})$ is the $1 \times M$ row vector of translog variables written for each observation $i = 1, ..., N$ and y_i is the logarithm of the normalized relative total cost for the individual bank i, while $\boldsymbol{\beta} = (\beta_1, \beta_2, ..., \beta_M)^T$ is the column vector of the translog coefficients that define the technology of the frontier. Given the model's assumptions, $\exp(-v_i) = r_i$ is the measure of bank efficiency.

In order to complete the specification of the statistical model and proceed to the empirical work, we need to choose the priors[6]. Following Koop, Osiewalski and Steel (1994), we choose:

- a non-informative prior on β: $\pi(\beta) \propto 1$.
- a gamma[7] prior[8] for σ_u^{-2}: $\pi(\sigma_u^{-2}) = f_G(\sigma_u^{-2}|\frac{\tau}{2}, \frac{s_p^2}{2})$. By setting $\tau = 1$ and $s_p^2 = 0.10$ we choose a weak prior on σ_u^2.
- a gamma prior for λ^{-1}: $\pi(\lambda^{-1}) = f_G(\lambda^{-1}|1, -\ln(r^*))$, where r^* is the prior mean for efficiency. We set r^* equal to 0.875[9] for all countries.

[6]by choosing informative priors for λ^{-1} and σ_u^{-2}, the posterior is ensured to be proper (integrate to one).
[7]where $f_G(.|\nu_1, \nu_2)$ is a gamma density with mean ν_1/ν_2 and variance ν_1/ν_2^2
[8]following Fernandez, Osiewalski, and Steel (1997)
[9]following Koop, Osiewalski and Steel (1994) and van den Broek, Koop, Osiewalski and Steel (1994)

The full conditional densities for this stochastic frontier model are also provided by Koop, Osiewalski and Steel (1994):

- $\boldsymbol{\beta}|\text{data}, \mathbf{v}, \sigma_u^2, \lambda \sim N(\widehat{\boldsymbol{\beta}}, (\mathrm{X}^T\mathrm{X})^{-1}\sigma_u^2)$, where $\widehat{\boldsymbol{\beta}} = (\mathrm{X}^T\mathrm{X})^{-1}\mathrm{X}^T\mathbf{y}^*$, with $\mathbf{y}^* = \mathbf{y} - \mathbf{v}$.
- $\sigma_u^{-2}|\text{data}, \mathbf{v}, \boldsymbol{\beta}, \lambda$ is gamma: $f_G(\sigma_u^{-2}|\frac{N+\tau-2}{2}, \frac{SSE+s_p^2}{2})$, where $SSE = (\mathbf{y}^* - \mathrm{X}\widehat{\boldsymbol{\beta}})^T(\mathbf{y}^* - \mathrm{X}\widehat{\boldsymbol{\beta}})$.
- $\lambda^{-1}|\text{data}, \mathbf{v}, \boldsymbol{\beta}, \sigma_u^2$ is gamma: $f_G(\lambda^{-1}|N+1, \mathbf{v}^T\mathbf{i_N} - \ln(r^*))$, where $\mathbf{i_N}$ is a $N \times 1$ vector of ones.
- $\mathbf{v}|\text{data}, \boldsymbol{\beta}, \sigma_u^2, \lambda$ is drawn from a truncated normal distribution[10]: the inefficiency of each bank, $v_i \sim N(y_i - \mathbf{x_{i.}}\boldsymbol{\beta} - \frac{\sigma_u^2}{\lambda}, \sigma_u^2)\mathrm{I}(v_i > 0)$, where $\mathbf{v} = (v_1, ..., v_N)$, $i = 1, ..., N$ and $\mathrm{I}(v_i) > 0$ is an indicator function that takes the value 1 if $v_i > 0$ and 0 otherwise.

For all the results reported in this chapter, the Gibbs sampler is based on 5,000 burn in samples and 55,000 Markov Chain Monte Carlo iterations. As start up values, we use a vector of relatively small inefficiency parameters: $\mathbf{v}^{[\mathbf{0}]} = [0.05\ 0.05\ ...\ 0.05]^T$, where $\mathbf{v}$ is of dimension $N \times 1$ and a low $\sigma_u^{2[0]} = 0.01$. Results were not sensitive to the choice of starting values.

5.3 Empirical Results

As stated earlier, the purpose of this chapter is to identify the individual cost frontiers of the selected countries and determine the domestic banks' X-efficiency relative to these nation-specific frontiers [11]. When data allows for it, separate results are reported for small, medium, and large banks to allow for possible differences in technology by the size of the bank.

[10]following Jondrow at al.(1983)
[11]the second approach as categorized by Berger (2007).

Wherever there was a wide range in terms of bank size[12], we split the samples as follows:

- if total assets are higher than 1,000 million dollars, the bank is labeled as large[13].
- banks with total assets between 500 and 1,000 millions are of medium size.
- banks with total assets between 100 and 500 millions are considered small.

Tables 5.1 through 5.9 report the posterior mean and posterior standard deviation together with the 90% highest density region (HDR) for the technology parameters, not only for the national and pooled frontiers independent of size, but also for small, medium and large banks when possible.

One immediately sees the expected pattern that linear terms are much larger than interactions and quadratic terms in tables 5.1 through 5.9. This reflects the difference in means for the variables and is consistent with prior studies.

Recall that the frontier of interest specifies the relationship between cost and multiple inputs and outputs. This, and the fact that quite different parameter vectors may imply similar technologies during the region of interest in price/output space, makes direct interpretation somewhat challenging even for a single country. For this application with 14 countries, the interpretation is complicated even more, particularly since the interesting region for the technology varies by country (for example, wages in Germany far exceed those in Serbia).

In light of the challenges, figures 5.1 through 5.3, in which frontiers are drawn for each country to provide a broad assessment of the degree to which technologies appear to vary across countries. Holding loan/equity and security/equity variables constant at the median values of the pooled dataset, the figure is constructed by varying avwage/avrate between its minimum and maximum values.

[12] There are a multitude of approaches in the literature regarding bank size due to a lack of industry standard. The thresholds for size category can follow the recommendations of the nation's central bank (the common classes are very small, small, medium, large and very large or megabanks), or the researcher can establish his/her own cut-offs, depending on the availability of the data and the purpose of the investigation.

[13] the banks for which total assets are greater than 10 billion dollars are a special category of large banks that will be referred to as megabanks.

Table 5.1: Translog Parameters: Posterior Means and Standard Deviation, 90% H.D.R.*

Parameters	POOLED FRONTIER			
	ALL	SMALL	MEDIUM	LARGE
β_1	1.4610	1.3890	1.0520	1.5380
Post. S.D.	(0.0193)	(0.0336)	(0.0463)	(0.0347)
[$H.D.R.$]	[1.4290,1.493]	[1.3340,1.4450]	[0.9740,1.1260]	[1.4800,1.5950]
β_2	0.2800	0.1172	0.4336	0.2533
Post. S.D.	(0.01061)	(0.0186)	(0.0321)	(0.0184)
[$H.D.R.$]	[0.2626,0.2975]	[0.0867,0.1478]	[0.3817,0.4875]	[0.2233,0.2839]
β_3	0.0846	0.1459	0.0887	0.0361
Post. S.D.	(0.0029)	(0.0049)	(0.0081)	(0.0048)
[$H.D.R.$]	[0.0798,0.08939]	[0.1379,0.1539]	[0.0752,0.1018]	[0.0281,0.0440]
β_4	0.3882	0.3898	0.4575	0.3535
Post. S.D.	(0.0104)	(0.0162)	(0.0255)	(0.0202)
[$H.D.R.$]	[0.3711,0.4053]	[0.3633,0.4167]	[0.4173,0.5013]	[0.3204,0.3869]
β_5	0.0609	0.0745	0.0823	0.0549
Post. S.D.	(0.0020)	(0.0028)	(0.0054)	(0.0041)
[$H.D.R.$]	[0.0576,0.0641]	[0.0699,0.0790]	[0.0733,0.0911]	[0.0481,0.0616]
β_6	0.2668	0.2456	0.3201	0.3604
Post. S.D.	(0.0071)	(0.0114)	(0.0182)	(0.0130)
[$H.D.R.$]	[0.2552,0.2785]	[0.2270,0.2643]	[0.2902,0.3499]	[0.3392,0.3819]
β_7	0.0361	0.0417	0.0539	0.0359
Post. S.D.	(0.0008)	(0.0013)	(0.0021)	(0.0013)
[$H.D.R.$]	[0.0347,0.0374]	[0.0396,0.0439]	[0.0505,0.0574]	[0.0338,0.0380]
β_8	-0.05534	-0.0186	-0.1029	-0.0136
Post. S.D.	(0.0047)	(0.0073)	(0.0120)	(0.0088)
[$H.D.R.$]	[-0.0632,-0.0476]	[-0.0307,-0.0067]	[-0.1229,-0.0835]	[-0.0281,0.0009]
β_9	-0.0150	0.0105	0.0170	-0.0384
Post. S.D.	(0.0032)	(0.0055)	(0.0080)	(0.0052)
[$H.D.R.$]	[-0.0203,-0.0097]	[0.0015,0.0195]	[0.0037,0.0301]	[-0.0468,-0.0299]
β_{10}	-0.0144	0.0090	-0.0218	-0.0599
Post. S.D.	(0.0024)	(0.0035)	(0.0069)	(0.0049)
[$H.D.R.$]	[-0.0184,-0.0104]	[0.0032,0.0148]	[-0.0331,-0.0104]	[-0.0680,-0.0518]
Obs.	13970	5305	2881	5784
No. banks	2819	1479	927	1269

Notes: * Highest Density Region
Posterior moments are computed based on 50,000 points generated from the Gibbs sampling algorithm. The end points of the 90% confidence region are the 5^{th} and the 95^{th} percentiles of the posterior marginal densities.

Table 5.2: Translog Parameters: Posterior Means and Standard Deviation, 90% H.D.R.*

Parameters	CROATIA	DENMARK		
	ALL	ALL	SMALL	LARGE
β_1	1.8180	1.8810	0.4584	0.9195
Post. S.D.	(0.5494)	(0.2251)	(0.4047)	(0.3394)
$[H.D.R.]$	[0.9074,2.7080]	[1.5010,2.2390]	[-0.2088,1.1270]	[0.3653,1.4770]
β_2	-0.4263	-0.1706	0.4619	0.6751
Post. S.D.	(0.4902)	(0.1928)	(0.2374)	(0.2804)
$[H.D.R.]$	[-1.2420,0.3747]	[-0.4807,0.1521]	[0.0705,0.8520]	[0.2147,1.1340]
β_3	0.1572	0.1198	0.0960	-0.0521
Post. S.D.	(0.1232)	(0.0404)	(0.0470)	(0.0585)
$[H.D.R.]$	[-0.0456,0.3592]	[0.0521,0.1845]	[0.0187,0.1732]	[-0.1485,0.0433]
β_4	0.3659	0.1363	1.4770	0.3481
Post. S.D.	(0.6233)	(0.1369)	(0.3510)	(0.1921)
$[H.D.R.]$	[-0.6483,1.397]	[-0.0847,0.3645]	[0.9000,2.0540]	[0.0348,0.6652]
β_5	0.1287	-0.0370	-0.1055	0.0055
Post. S.D.	(0.1815)	(0.0281)	(0.0822)	(0.0373)
$[H.D.R.]$	[-0.1708,0.4235]	[-0.0831,0.0091]	[-0.2409,0.0293]	[-0.0568,0.0657]
β_6	0.7201	0.5137	1.0370	0.4752
Post. S.D.	(0.1331)	(0.0921)	(0.2397)	(0.1258)
$[H.D.R.]$	[0.5004,0.9384]	[0.3632,0.6670]	[0.6422,1.4300]	[0.2694,0.6814]
β_7	0.1043	0.03333	0.0302	0.0344
Post. S.D.	(0.0186)	(0.0104)	(0.0381)	(0.0160)
$[H.D.R.]$	[0.0737,0.1347]	[0.0160,0.0503]	[-0.0324,0.0926]	[0.0081,0.0609]
β_8	0.4844	0.3231	-0.2040	0.1543
Post. S.D.	(0.2693)	(0.0653)	(0.1001)	(0.0974)
$[H.D.R.]$	[0.0419,0.9305]	[0.2152,0.4290]	[-0.3668,-0.0379]	[-0.0047,0.3150]
β_9	-0.1049	-0.1264	-0.1177	-0.1571
Post. S.D.	(0.0789)	(0.0348)	(0.0683)	(0.0627)
$[H.D.R.]$	[-0.2340,0.0248]	[-0.1836,-0.0689]	[-0.2307,-0.0051]	[-0.2592,-0.0533]
β_{10}	-0.3116	-0.1019	-0.4487	-0.1041
Post. S.D.	(0.0864)	(0.0340)	(0.1010)	(0.0373)
$[H.D.R.]$	[-0.4532,-0.1693]	[-0.1582,-0.0468]	[-0.6142,-0.2833]	[-0.1651,-0.0431]
Obs.	121	375	174	132
No. banks	26	78	51	39

Notes: * Highest Density Region
Posterior moments are computed based on 50,000 points generated from the Gibbs sampling algorithm. The end points of the 90% confidence region are the 5^{th} and the 95^{th} percentiles of the posterior marginal densities.

Table 5.3: Translog Parameters: Posterior Means and Standard Deviation, 90% H.D.R.*

Parameters	GERMANY			
	ALL	SMALL	MEDIUM	LARGE
β_1	1.3770	1.6360	1.1200	1.0560
Post. S.D.	(0.0286)	(0.0351)	(0.0658)	(0.0600)
$[H.D.R.]$	[1.3300,1.4240]	[1.5770,1.6920]	[1.0090,1.2250]	[0.9561,1.1540]
β_2	0.5245	0.2014	0.5451	0.5215
Post. S.D.	(0.0271)	(0.0407)	(0.0746)	(0.0477)
$[H.D.R.]$	[0.4801,0.5693]	[0.1367,0.2699]	[0.4239,0.6691]	[0.4444,0.6011]
β_3	-0.0133	0.0894	0.0530	-0.0455
Post. S.D.	(0.0082)	(0.0155)	(0.0230)	(0.0112)
$[H.D.R.]$	[-0.0268,0.0002]	[0.0634,0.1145]	[0.0150,0.0910]	[-0.0643,-0.0274]
β_4	0.5231	0.4054	0.6803	0.6888
Post. S.D.	(0.0135)	(0.0143)	(0.0476)	(0.0377)
$[H.D.R.]$	[0.5012,0.5455]	[0.3822,0.4293]	[0.6045,0.7605]	[0.6284,0.7521]
β_5	0.0486	0.0650	0.0354	0.0282
Post. S.D.	(0.0022)	(0.0026)	(0.0091)	(0.0068)
$[H.D.R.]$	[0.0449,0.0521]	[0.0606,0.0693]	[0.0202,0.0502]	[0.0166,0.0389]
β_6	0.4973	0.3741	0.5194	0.6028
Post. S.D.	(0.0133)	(0.0142)	(0.0295)	(0.0195)
$[H.D.R.]$	[0.4755,0.5192]	[0.3510,0.3976]	[0.4709,0.5677]	[0.5707,0.6349]
β_7	0.0298	0.0472	0.0257	0.0277
Post. S.D.	(0.0014)	(0.0027)	(0.0024)	(0.0019)
$[H.D.R.]$	[0.0275,0.0321]	[0.0429,0.0516]	[0.0217,0.0296]	[0.0245,0.0308]
β_8	-0.0780	-0.0142	-0.1254	-0.0825
Post. S.D.	(0.0076)	(0.0105)	(0.0258)	(0.0153)
$[H.D.R.]$	[-0.0906,-0.0654]	[-0.0318,0.0027]	[-0.1682,-0.0834]	[-0.1082,-0.0579]
β_9	-0.0745	-0.0556	-0.0530	-0.0427
Post. S.D.	(0.0073)	(0.0115)	(0.0146)	(0.0109)
$[H.D.R.]$	[-0.0865,-0.0625]	[-0.0748,-0.0368]	[-0.0771,-0.0289]	[-0.0608,-0.0248]
β_{10}	-0.1276	-0.0802	-0.1349	-0.1754
Post. S.D.	(0.0048)	(0.0050)	(0.0111)	(0.0070)
$[H.D.R.]$	[-0.1354,-0.1197]	[-0.0885,-0.0720]	[-0.1532,-0.1167]	[-0.1869,-0.1639]
Obs.	8668	3111	2021	3536
No. banks	1471	823	562	630

Notes: $*$ Highest Density Region
Posterior moments are computed based on 50,000 points generated from the Gibbs sampling algorithm. The end points of the 90% confidence region are the 5^{th} and the 95^{th} percentiles of the posterior marginal densities.

Table 5.4: Translog Parameters: Posterior Means and Standard Deviation, 90% H.D.R.*

Parameters	FRANCE		NETHERLANDS	
	ALL	LARGE	ALL	LARGE
β_1	-0.5787	-0.6682	1.9450	1.9270
Post. S.D.	(0.1357)	(0.1344)	(0.2310)	(0.2684)
$[H.D.R.]$	[-0.7989,-0.3537]	[-0.8911,-0.4498]	[1.5550,2.3130]	[1.4690,2.3460]
β_2	1.8690	1.9860	0.5145	0.5258
Post. S.D.	(0.1120)	(0.1441)	(0.1627)	(0.1738)
$[H.D.R.]$	[1.6850,2.0520]	[1.7520,2.2260]	[0.2479,0.7837]	[0.2421,0.8107]
β_3	-0.1508	-0.2300	-0.0226	-0.0720
Post. S.D.	(0.0244)	(0.0331)	(0.0600)	(0.0665)
$[H.D.R.]$	[-0.1911,-0.1108]	[-0.2863,-0.1778]	[-0.1226,0.0747]	[-0.1816,0.0372]
β_4	1.2550	1.2140	-0.0437	-0.0432
Post. S.D.	(0.0855)	(0.0811)	(0.1077)	(0.1213)
$[H.D.R.]$	[1.1130,1.3960]	[1.0820,1.3500]	[-0.2196,0.1357]	[-0.2411,0.1581]
β_5	-0.0019	0.0086	0.0840	0.0839
Post. S.D.	(0.0175)	(0.0162)	(0.0187)	(0.0225)
$[H.D.R.]$	[-0.0310,0.0269]	[-0.0181,0.0350]	[0.0527,0.1144]	[0.0456,0.1194]
β_6	0.2237	0.3135	-0.1013	-0.1045
Post. S.D.	(0.0366)	(0.0423)	(0.0996)	(0.1154)
$[H.D.R.]$	[0.1638,0.2839]	[0.2441,0.3837]	[-0.2663,0.0627]	[-0.2914,0.0851]
β_7	0.0104	0.0115	0.0090	0.0143
Post. S.D.	(0.0033)	(0.0034)	(0.0186)	(0.0197)
$[H.D.R.]$	[0.0049,0.0156]	[0.0058,0.0169]	[-0.0218,0.0391]	[-0.0185,0.0460]
β_8	-0.5363	-0.4847	-0.0266	-0.0184
Post. S.D.	(0.0353)	(0.0511)	(0.0511)	(0.0572)
$[H.D.R.]$	[-0.5939,-0.4779]	[-0.5686,-0.4008]	[-0.1099,0.0585]	[-0.1108,0.0770]
β_9	-0.0062	-0.0195	0.0998	0.0991
Post. S.D.	(0.0131)	(0.0148)	(0.0462)	(0.0489)
$[H.D.R.]$	[-0.0278,0.0156]	[-0.0442,0.0045]	[0.0234,0.1755]	[0.0184,0.1790]
β_{10}	-0.0795	-0.1027	0.0312	0.0272
Post. S.D.	(0.0134)	(0.0148)	(0.0346)	(0.0409)
$[H.D.R.]$	[-0.1016,-0.0577]	[-0.1270,-0.0786]	[-0.0262,0.0876]	[-0.0415,0.0922]
Obs.	527	452	134	118
No. banks	171	150	36	33

Notes: * Highest Density Region
Posterior moments are computed based on 50,000 points generated from the Gibbs sampling algorithm. The end points of the 90% confidence region are the 5^{th} and the 95^{th} percentiles of the posterior marginal densities.

Table 5.5: Translog Parameters: Posterior Means and Standard Deviation, 90% H.D.R.*

Parameters	ITALY			
	ALL	SMALL	MEDIUM	LARGE
β_1	0.6475	0.1996	0.3114	1.0020
Post. S.D.	(0.0776)	(0.2125)	(0.1830)	(0.0875)
$[H.D.R.]$	[0.5165,0.7708]	[-0.1494,0.5478]	[0.0125,0.6137]	[0.8534,1.1400]
β_2	0.6200	0.8928	0.7452	0.5303
Post. S.D.	(0.0733)	(0.1653)	(0.1513)	(0.0861)
$[H.D.R.]$	[0.5021,0.7420]	[0.6227,1.1640]	[0.4966,0.9955]	[0.3942,0.6767]
β_3	0.0789	0.0022	0.0803	0.0888
Post. S.D.	(0.0206)	(0.0386)	(0.0328)	(0.0310)
$[H.D.R.]$	[0.0447,0.1125]	[-0.0616,0.0654]	[0.0252,0.1330]	[0.0372,0.1388]
β_4	0.2138	0.3796	0.2912	0.1235
Post. S.D.	(0.0433)	(0.1765)	(0.1193)	(0.0481)
$[H.D.R.]$	[0.1453,0.2879]	[0.0893,0.6690]	[0.0947,0.4871]	[0.0466,0.2050]
β_5	0.1272	0.1540	0.1724	0.0975
Post. S.D.	(0.0065)	(0.0388)	(0.0184)	(0.0082)
$[H.D.R.]$	[0.1163,0.1375]	[0.0908,0.2182]	[0.1420,0.2023]	[0.0840,0.1108]
β_6	0.3584	0.2859	0.7617	0.2843
Post. S.D.	(0.0286)	(0.0911)	(0.0588)	(0.0385)
$[H.D.R.]$	[0.3112,0.4054]	[0.1344,0.4348]	[0.6648,0.8589]	[0.2209,0.3473]
β_7	0.0252	0.1348	0.0561	0.0122
Post. S.D.	(0.0028)	(0.0144)	(0.0103)	(0.0037)
$[H.D.R.]$	[0.0206,0.0298]	[0.1107,0.1579]	[0.0388,0.0725]	[0.0062,0.0183]
β_8	0.0929	-0.0052	0.0136	0.1238
Post. S.D.	(0.0240)	(0.0659)	(0.0629)	(0.0303)
$[H.D.R.]$	[0.0529,0.1315]	[-0.1135,0.1036]	[-0.0904,0.1173]	[0.0729,0.1729]
β_9	-0.0453	0.0410	-0.1323	-0.0212
Post. S.D.	(0.0116)	(0.0435)	(0.0381)	(0.0163)
$[H.D.R.]$	[-0.0644,-0.0262]	[-0.0299,0.1135]	[-0.1943,-0.0698]	[-0.0479,0.00564]
β_{10}	-0.0772	-0.0586	-0.2211	-0.0830
Post. S.D.	(0.0097)	(0.0366)	(0.0257)	(0.0125)
$[H.D.R.]$	[-0.0931,-0.0611]	[-0.1180,0.0022]	[-0.2632,-0.1790]	[-0.1037,-0.0623]
Obs.	1818	745	355	718
No. banks	561	287	158	215

Notes: * Highest Density Region
Posterior moments are computed based on 50,000 points generated from the Gibbs sampling algorithm. The end points of the 90% confidence region are the 5^{th} and the 95^{th} percentiles of the posterior marginal densities.

Table 5.6: Translog Parameters: Posterior Means and Standard Deviation, 90% H.D.R.*

Parameters	POLAND	ROMANIA	SERBIA	SLOVENIA
	ALL	ALL	ALL	ALL
β_1	1.2580	2.3330	2.9580	0.6707
Post. S.D.	(0.3549)	(0.1742)	(0.4669)	(0.3750)
$[H.D.R.]$	[0.6735,1.8410]	[2.0440,2.6160]	[2.2190,3.7500]	[0.05512,1.2820]
β_2	-0.2465	0.0511	1.0940	-0.1811
Post. S.D.	(0.1380)	(0.1946)	(0.3519)	(0.3340)
$[H.D.R.]$	[-0.4733,-0.0191]	[-0.2701,0.3711]	[0.4963,1.6450]	[-0.7262,0.3687]
β_3	-0.0062	-0.0260	0.0342	0.2513
Post. S.D.	(0.0288)	(0.0558)	(0.1216)	(0.1121)
$[H.D.R.]$	[-0.0536,0.0407]	[-0.1190,0.0662]	[-0.1823,0.2126]	[0.0668,0.4333]
β_4	1.5740	0.3902	0.1938	1.3100
Post. S.D.	(0.4274)	(0.1263)	(0.3922)	(0.3892)
$[H.D.R.]$	[0.8706,2.2720]	[0.1893,0.6026]	[-0.4239,0.8529]	[0.6691,1.9480]
β_5	-0.3970	0.0400	0.0533	-0.1808
Post. S.D.	(0.1306)	(0.0542)	(0.1419)	(0.1091)
$[H.D.R.]$	[-0.6095,-0.1823]	[-0.0500,0.1277]	[-0.1911,0.2741]	[-0.3599,-0.0019]
β_6	0.1195	0.2221	0.2612	-0.0111
Post. S.D.	(0.1268)	(0.0972)	(0.1681)	(0.2938)
$[H.D.R.]$	[-0.0881,0.3269]	[0.0609,0.3809]	[-0.0024,0.5469]	[-0.4900,0.4710]
β_7	0.0236	0.0149	0.0203	0.2864
Post. S.D.	(0.0161)	(0.0127)	(0.0169)	(0.0793)
$[H.D.R.]$	[-0.0028,0.0502]	[-0.0060,0.0357]	[-0.0061,0.0495]	[0.1561,0.4173]
β_8	0.2495	0.1920	-0.1436	0.0378
Post. S.D.	(0.0688)	(0.0881)	(0.2447)	(0.1714)
$[H.D.R.]$	[0.1357,0.3625]	[0.0476,0.3366]	[-0.5399,0.2611]	[-0.2435,0.3205]
β_9	-0.0230	0.0059	0.0115	0.2618
Post. S.D.	(0.0445)	(0.0401)	(0.0620)	(0.1604)
$[H.D.R.]$	[-0.0964,0.0501]	[-0.0594,0.0722]	[-0.0887,0.1142]	[-0.0026,0.5253]
β_{10}	0.0581	-0.0685	-0.0438	-0.1004
Post. S.D.	(0.0697)	(0.0453)	(0.0667)	(0.1691)
$[H.D.R.]$	[-0.0555,0.1729]	[-0.1427,0.0062]	[-0.1511,0.0673]	[-0.3773,0.1784]
Obs.	93	104	80	84
No. banks	28	23	25	17

Notes: * Highest Density Region
Posterior moments are computed based on 50,000 points generated from the Gibbs sampling algorithm. The end points of the 90% confidence region are the 5^{th} and the 95^{th} percentiles of the posterior marginal densities.

Table 5.7: Translog Parameters: Posterior Means and Standard Deviation, 90% H.D.R.*

Parameters	POOLED FRONTIER		SWEDEN	
	ALL	SMALL	ALL	SMALL
β_1	1.4610	1.389	0.2531	-0.0807
Post. S.D.	(0.0193)	(0.0336)	(0.4173)	(0.5433)
$[H.D.R.]$	[1.429,1.493]	[1.3340,1.4450]	[-0.4380,0.9333]	[-0.9832,0.8128]
β_2	0.2800	0.1172	-0.5513	-0.2416
Post. S.D.	(0.01061)	(0.0186)	(0.2126)	(0.2426)
$[H.D.R.]$	[0.2626,0.2975]	[0.0867,0.1478]	[-0.8991,-0.1966]	[-0.6398,0.1571]
β_3	0.0846	0.1459	0.2098	0.2821
Post. S.D.	(0.0029)	(0.0049)	(0.0417)	(0.0510)
$[H.D.R.]$	[0.0798,0.08939]	[0.1379,0.1539]	[0.1407,0.2780]	[0.1975,0.3654]
β_4	0.3882	0.3898	2.2810	2.3630
Post. S.D.	(0.0104)	(0.0162)	(0.3713)	(0.5596)
$[H.D.R.]$	[0.3711,0.4053]	[0.3633,0.4167]	[1.6730,2.8930]	[1.4390,3.2850]
β_5	0.0609	0.0745	-0.5057	-0.2816
Post. S.D.	(0.0020)	(0.0028)	(0.0844)	(0.1610)
$[H.D.R.]$	[0.0576,0.0641]	[0.0699,0.0790]	[-0.6447,-0.3684]	[-0.5456,-0.0169]
β_6	0.2668	0.2456	0.2813	0.2570
Post. S.D.	(0.0071)	(0.0114)	(0.0799)	(0.0950)
$[H.D.R.]$	[0.2552,0.2785]	[0.2270,0.2643]	[0.1507,0.4133]	[0.1014,0.4132]
β_7	0.0361	0.0417	0.0238	0.0333
Post. S.D.	(0.0008)	(0.0013)	(0.0043)	(0.0056)
$[H.D.R.]$	[0.0347, 0.0374]	[0.0396,0.0439]	[0.0166,0.0309]	[0.0240,0.0424]
β_8	-0.05534	-0.0186	0.2042	-0.1891
Post. S.D.	(0.0047)	(0.0073)	(0.0753)	(0.1221)
$[H.D.R.]$	[-0.0632, -0.0476]	[-0.0307,-0.0067]	[0.0798,0.3282]	[-0.3909,0.0124]
β_9	-0.0150	0.0105	0.0429	-0.0023
Post. S.D.	(0.0032)	(0.0055)	(0.0187)	(0.0233)
$[H.D.R.]$	[-0.0203,-0.0097]	[0.0015,0.0195]	[0.0121,0.0736]	[-0.0408,0.0358]
β_{10}	-0.0144	0.0090	-0.1121	-0.0198
Post. S.D.	(0.0024)	(0.0035)	(0.0323)	(0.0477)
$[H.D.R.]$	[-0.0184,-0.0104]	[0.0032,0.0148]	[-0.1656,-0.0591]	[-0.0980,0.0587]
Obs.	13970	5305	344	235
No. banks	2819	1479	61	48

Notes: * Highest Density Region
Posterior moments are computed based on 50,000 points generated from the Gibbs sampling algorithm. The end points of the 90% confidence region are the 5^{th} and the 95^{th} percentiles of the posterior marginal densities.

Table 5.8: Translog Parameters: Posterior Means and Standard Deviation, 90% H.D.R.*

Parameters	SWITZERLAND			
	ALL	SMALL	MEDIUM	LARGE
β_1	0.9152	0.7389	-0.8604	2.2740
Post. S.D.	(0.1161)	(0.1353)	(0.3917)	(0.1739)
$[H.D.R.]$	[0.7262,1.1090]	[0.5205,0.9641]	[-1.4990,-0.2118]	[1.9900,2.5610]
β_2	0.1683	0.0597	1.7960	-0.5788
Post. S.D.	(0.0655)	(0.0680)	(0.2537)	(0.1132)
$[H.D.R.]$	[0.0614,0.2773]	[-0.0491,0.1733]	[1.3640,2.1980]	[-0.7594,-0.3881]
β_3	0.1284	0.1650	-0.1577	0.2445
Post. S.D.	(0.0117)	(0.0115)	(0.0438)	(0.0248)
$[H.D.R.]$	[0.1092,0.1475]	[0.1457,0.1832]	[-0.2270,-0.0823]	[0.2026,0.2839]
β_4	0.3608	0.4420	0.9494	-0.0922
Post. S.D.	(0.0515)	(0.0624)	(0.1287)	(0.1186)
$[H.D.R.]$	[0.2747,0.4447]	[0.3376,0.5431]	[0.7370,1.1580]	[-0.2873,0.1035]
β_5	0.0522	0.0466	0.0531	0.1235
Post. S.D.	(0.0058)	(0.0062)	(0.0177)	(0.0192)
$[H.D.R.]$	[0.0425,0.0617]	[0.0363,0.0566]	[0.0230,0.0813]	[0.0911,0.1542]
β_6	0.1466	0.0967	0.5830	0.4251
Post. S.D.	(0.0399)	(0.0475)	(0.1606)	(0.0917)
$[H.D.R.]$	[0.0815,0.2130]	[0.0197,0.1758]	[0.3206,0.8471]	[0.2735,0.5738]
β_7	-0.0053	-0.0173	-0.0009	0.0341
Post. S.D.	(0.0027)	(0.0035)	(0.0118)	(0.0038)
$[H.D.R.]$	[-0.0097,-0.0009]	[-0.0230,-0.0117]	[-0.0206,0.0180]	[0.0276,0.0401]
β_8	-0.0224	-0.0247	-0.3870	0.0565
Post. S.D.	(0.0184)	(0.0203)	(0.0600)	(0.0402)
$[H.D.R.]$	[-0.0525,0.0081]	[-0.0581,0.0086]	[-0.4828,-0.2847]	[-0.0095,0.1227]
β_9	-0.0042	-0.0475	-0.1675	-0.0808
Post. S.D.	(0.0176)	(0.0177)	(0.0599)	(0.0350)
$[H.D.R.]$	[-0.0335,0.0244]	[-0.0767,-0.0188]	[-0.2650,-0.0686]	[-0.1382,-0.0231]
β_{10}	-0.0733	-0.0658	-0.1144	-0.0544
Post. S.D.	(0.0085)	(0.0118)	(0.0391)	(0.0228)
$[H.D.R.]$	[-0.0871,-0.0594]	[-0.0853,-0.0467]	[-0.1787,-0.0508]	[-0.0898,-0.0150]
Obs.	1188	749	201	238
No. banks	221	170	69	44

Notes: * Highest Density Region
Posterior moments are computed based on 50,000 points generated from the Gibbs sampling algorithm.
The end points of the 90% confidence region are the 5^{th} and the 95^{th} percentiles of the posterior marginal densities.

Table 5.9: Translog Parameters: Posterior Means and Standard Deviation, 90% H.D.R.*

Parameters	TURKEY	UNITED KINGDOM		
	ALL	ALL	SMALL	LARGE
β_1	1.4140	1.5440	1.4880	1.6520
Post. S.D.	(0.1965)	(0.1427)	(0.2153)	(0.1806)
$[H.D.R.]$	[1.0990,1.7460]	[1.2830,1.7520]	[1.1230,1.8310]	[1.3370,1.9280]
β_2	0.3001	0.3522	0.6687	0.1468
Post. S.D.	(0.2443)	(0.0836)	(0.2470)	(0.1186)
$[H.D.R.]$	[-0.1021,0.7007]	[0.2165,0.4907]	[0.2638,1.0720]	[-0.0434,0.3441]
β_3	0.2389	-0.0085	-0.1146	0.0074
Post. S.D.	(0.0995)	(0.0266)	(0.1441)	(0.1441)
$[H.D.R.]$	[0.0754,0.4024]	[-0.0537,0.0333]	[-0.3541,0.1228]	[-0.0452,0.0564]
β_4	0.6709	0.2576	-0.0879	0.1676
Post. S.D.	(0.1959)	(0.0415)	(0.2410)	(0.0589)
$[H.D.R.]$	[0.3388,0.9804]	[0.1900,0.3264]	[-0.4823,0.3085]	[0.0725,0.2647]
β_5	0.0487	0.0623	0.4714	0.0790
Post. S.D.	(0.0600)	(0.0135)	(0.1482)	(0.0141)
$[H.D.R.]$	[-0.0500,0.1475]	[0.0402,0.0844]	[0.2292,0.7148]	[0.0556,0.1020]
β_6	0.0724	0.3191	0.2537	0.3176
Post. S.D.	(0.2163)	(0.0444)	(0.1288)	(0.0585)
$[H.D.R.]$	[-0.2826,0.4293]	[0.2461,0.3918]	[0.0407,0.4651]	[0.2221,0.4145]
β_7	-0.0198	0.0211	0.0109	0.0213
Post. S.D.	(0.0699)	(0.0058)	(0.0279)	(0.0060)
$[H.D.R.]$	[-0.1352,0.0946]	[0.0115,0.0307]	[-0.0354,0.0569]	[0.0114,0.0311]
β_8	0.3035	0.0615	0.1040	0.1217
Post. S.D.	(0.1216)	(0.0280)	(0.2158)	(0.0347)
$[H.D.R.]$	[0.0990,0.5002]	[0.0158,0.1077]	[-0.2514,0.4573]	[0.0648,0.1784]
β_9	-0.1627	-0.1003	-0.0087	-0.0853
Post. S.D.	(0.1590)	(0.0250)	(0.1220)	(0.0285)
$[H.D.R.]$	[-0.4262,0.0981]	[-0.1411,-0.0591]	[-0.2088,0.1913]	[-0.1321,-0.0387]
β_{10}	-0.0650	-0.0711	-0.1069	-0.0774
Post. S.D.	(0.1225)	(0.0171)	(0.0700)	(0.0213)
$[H.D.R.]$	[-0.2635,0.1381]	[-0.0991,-0.0429]	[-0.2212,0.0073]	[-0.1125,-0.0426]
Obs.	84	350	87	226
No. banks	18	85	25	60

Notes: $*$ Highest Density Region
Posterior moments are computed based on 50,000 points generated from the Gibbs sampling algorithm. The end points of the 90% confidence region are the 5^{th} and the 95^{th} percentiles of the posterior marginal densities.

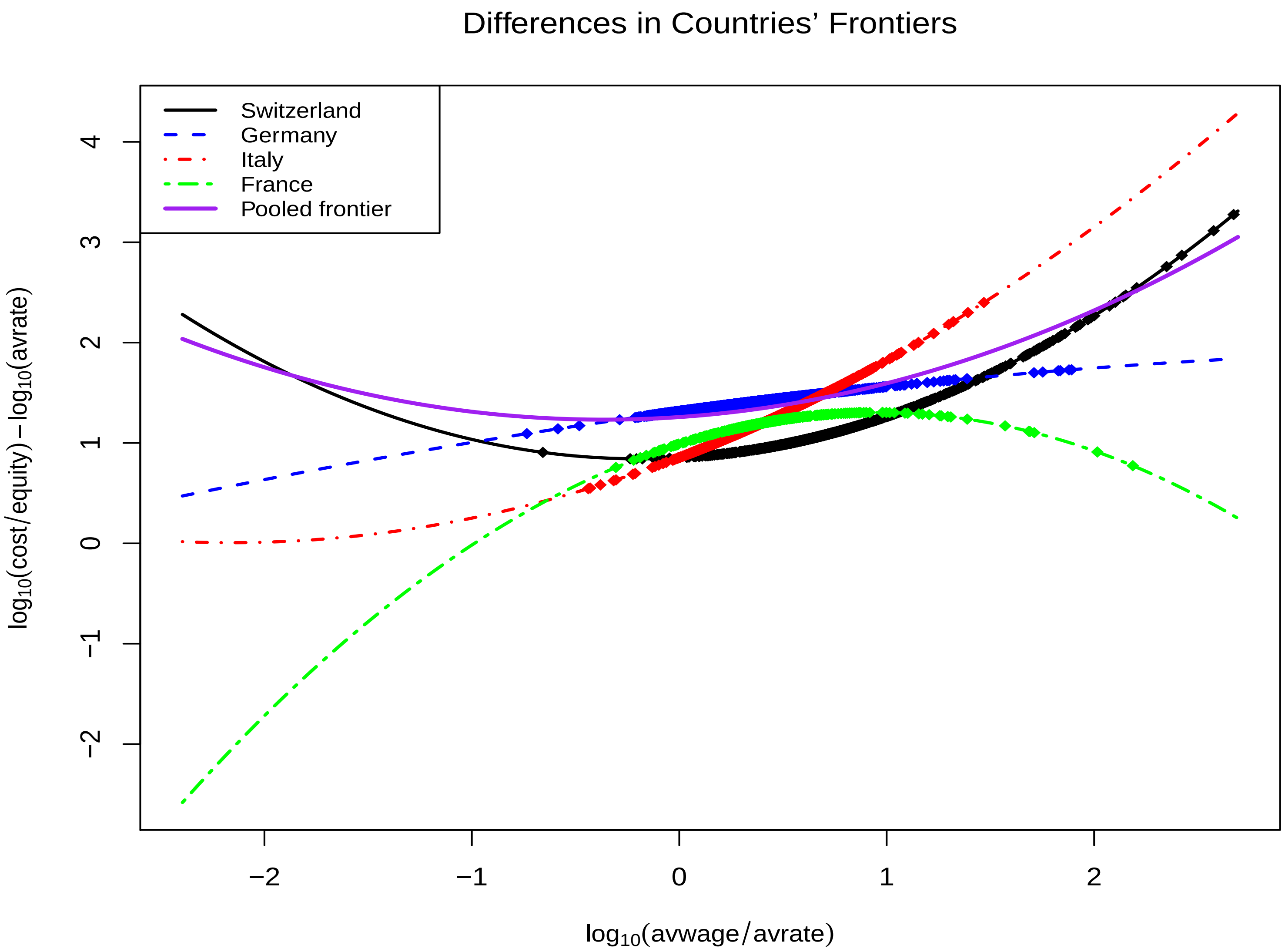


Figure 5.1: Switzerland, Germany, Italy, France and the Pooled Frontiers Drawn at the Sample Median Values for loan/equity and security/equity.

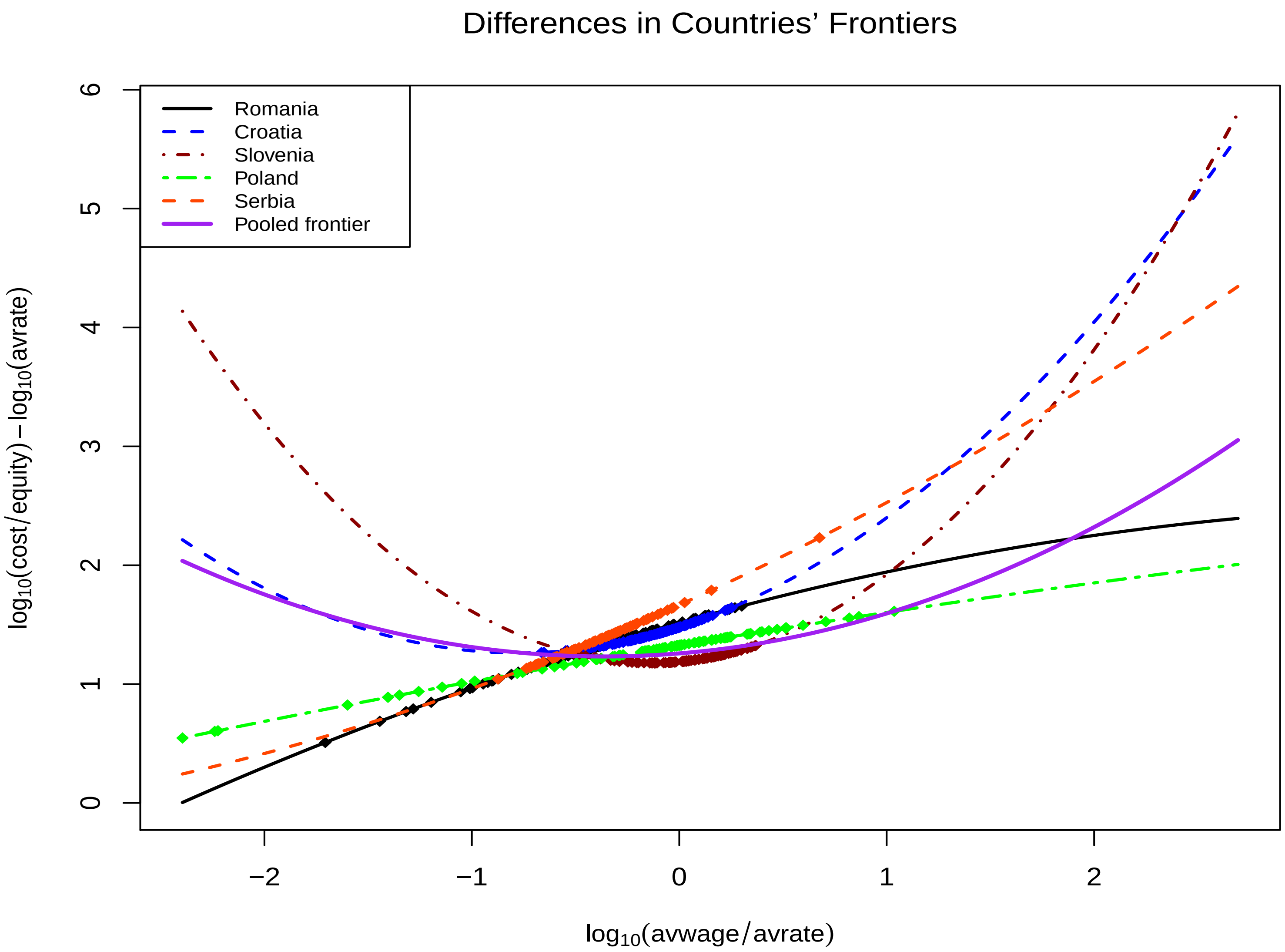


Figure 5.2: Romania, Croatia, Slovenia, Poland, Serbia and Pooled Frontiers Drawn at the Sample Median Values for loan/equity and security/equity.

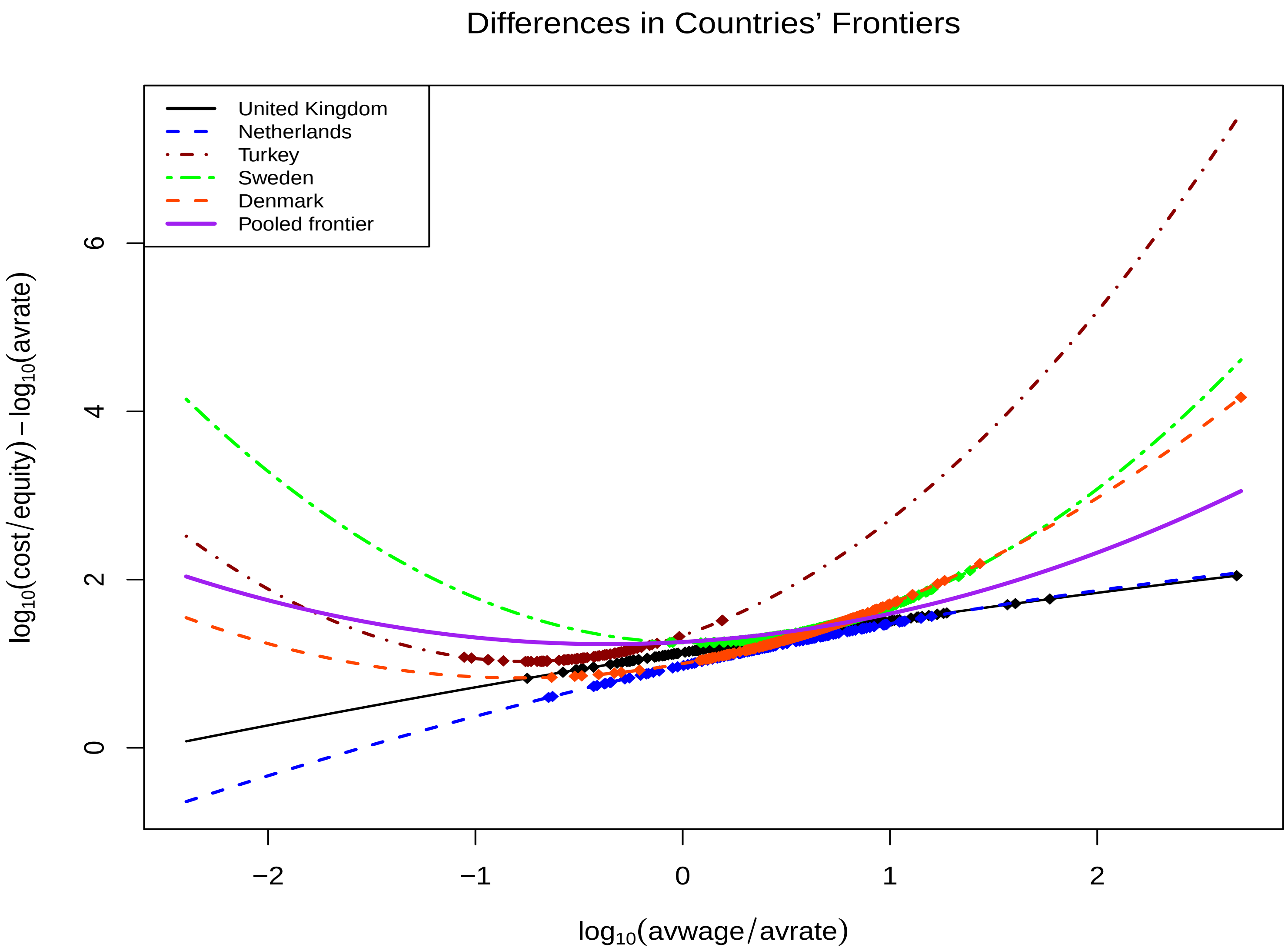


Figure 5.3: United Kingdom, Netherlands, Turkey, Sweden, Denmark and Pooled Frontiers Drawn at the Sample Median Values for loan/equity and security/equity.

Because the frontiers are drawn based on the range of the pooled data, each country's frontier points are also included on the graph. We look at all banks in each country, without differentiating across bank sizes. Keeping in mind the fact that these are two dimensional representations of four dimensional graphs obtained by fixing certain variables, we can still see that there are differences in frontier shapes across the selected countries.

Germany's cost frontier is closest to the pooled frontier, which is not surprising considering that more than half of the pooled observations are coming from the German banking system. Higher deviations from the pooled frontier in the overall shapes are observed for Romania, Serbia, Croatia, France, Italy, Turkey or Switzerland. It is also worth noting that several of the frontiers clearly violate the concavity property of the cost function.

Before leaving the discussion of parameter values, some discussion of the posterior standard deviations and highest density regions is in order. Not surprisingly, the translog parameters results tables show that the 90 percent highest density regions are narrower and the posterior standard deviation is smaller in the case of the countries with more observations like Germany, Italy or Switzerland.

For countries like Romania, Serbia, Poland, Turkey that have 100 or less bank-year observations, the translog parameters exhibit wider 90 percent highest density regions and bigger posterior standard deviations. To illustrate this finding, we show the posterior marginal densities for the translog parameters of the Romanian and the pooled cost frontiers side by side in figures 5.4 through 5.8. They correspond to the results from tables 5.1 and 5.6. In general, irrespective of country and sample size, the marginal posterior distributions of the translog parameters are smooth and do look normal. All the posterior marginal densities included in this thesis were generated with R software, using the default settings of the density function. According to the software's website[14], the density.default algorithm "disperses the mass of the empirical distribution function over a regular grid of at least 512 points and then uses

[14]http://stat.ethz.ch/R-manual/R-devel/library/stats/html/density.html

the fast Fourier transform to convolve this approximation with a discretized version of the kernel and then uses linear approximation to evaluate the density at the specified points". The bandwidth is determined[15] by the formula: $b = \frac{\max(x)-\min(x)}{2(1+\log_2 n)}$, where n is the number of data points.

When it comes to size, we observe that medium and large German banks have very similar technologies (for the majority of the translog parameters, the posterior means are close in value) and drive the values of the overall frontier, while for the pooled frontiers, the technologies for medium and large banks are not that close anymore. Very different technologies across sizes were identified in the cases of Switzerland, Italy and Denmark. The samples for Netherlands, Romania, Poland, Slovenia, Turkey and France are dominated by observations large banks, Croatia and Sweden have more small banks, while Serbia exhibits a more balanced sample and for these countries. Due to the relatively small number of observations for some bank categories, we focus on national frontiers, without splitting the datasets. United Kingdom and Denmark have a split set with more small and large banks that exhibit differences in technologies.

Figures 5.9 through 5.13 include the posterior marginal densities for the Italian translog parameters according to bank size in order to illustrate the differences found in technologies across bank sizes. While we cannot draw a general conclusion that one category is more or less similar to another in terms of technology, as is the case for German banks, the results for the overall Italian cost frontier independent of bank size seem to be driven in general by the large banks.

[15]Venables and Ripley (2002) offer more information on the procedure, but in essence it allows for a compromise between smoothing too much so that it gets rid of the true peaks and too little so that irrelevant humps remain (Crawley, 2007). Other references for the density estimation algorithm used can be found at the above mentioned web link.

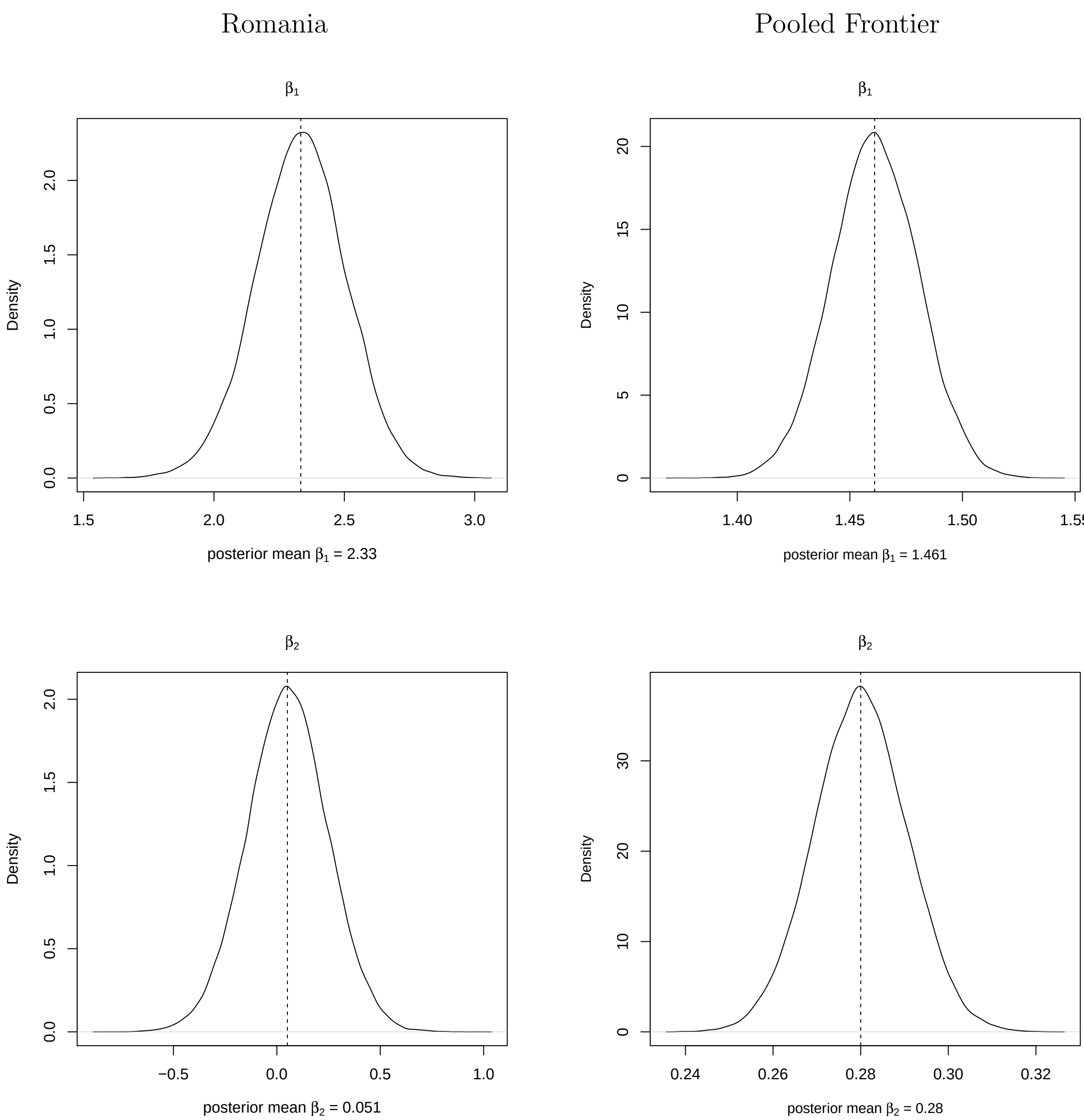


Figure 5.4: Posterior Marginal Densities for Translog Parameters β_1 and β_2.

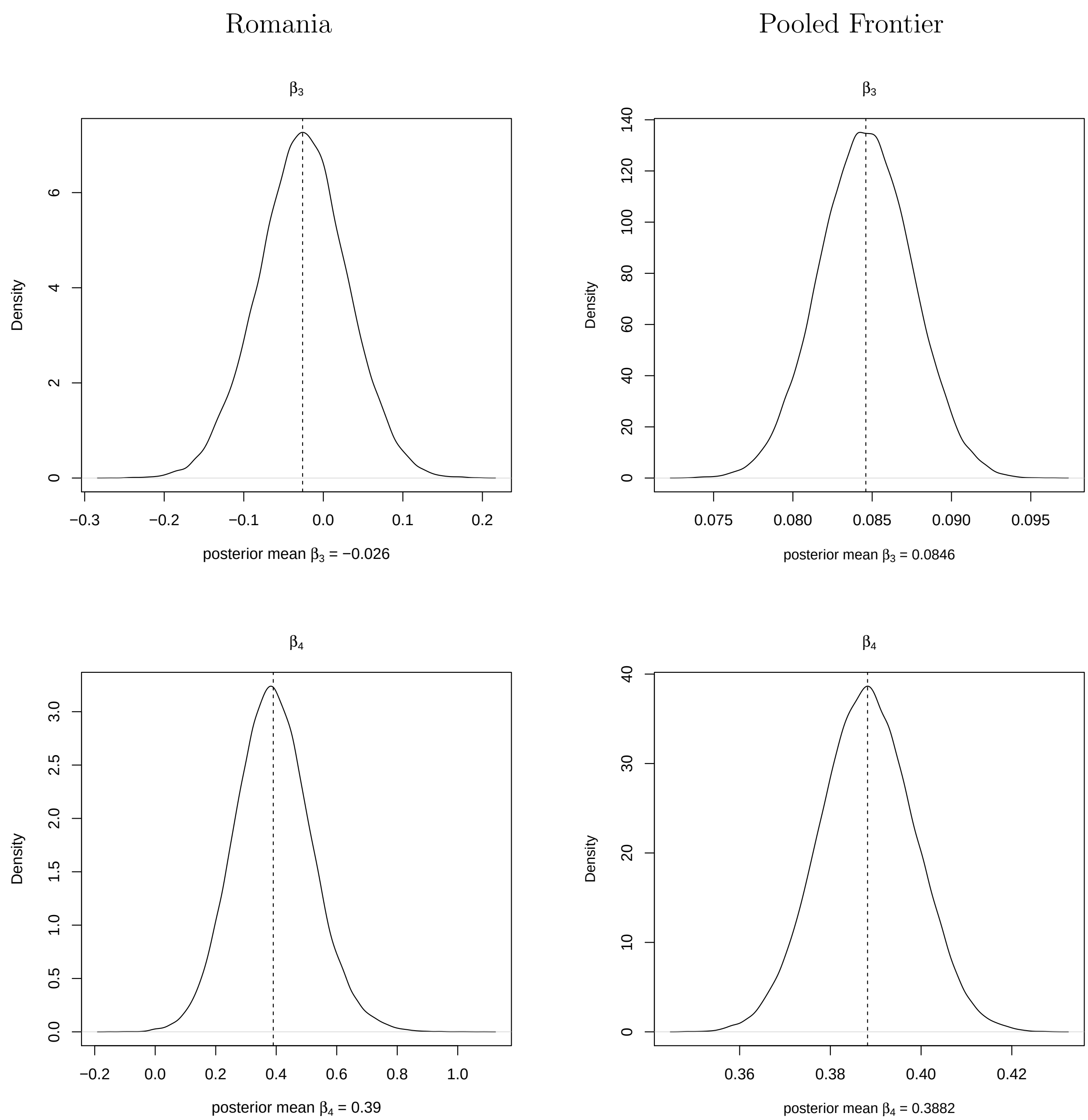


Figure 5.5: Posterior Marginal Densities for Translog Parameters β_3 and β_4.

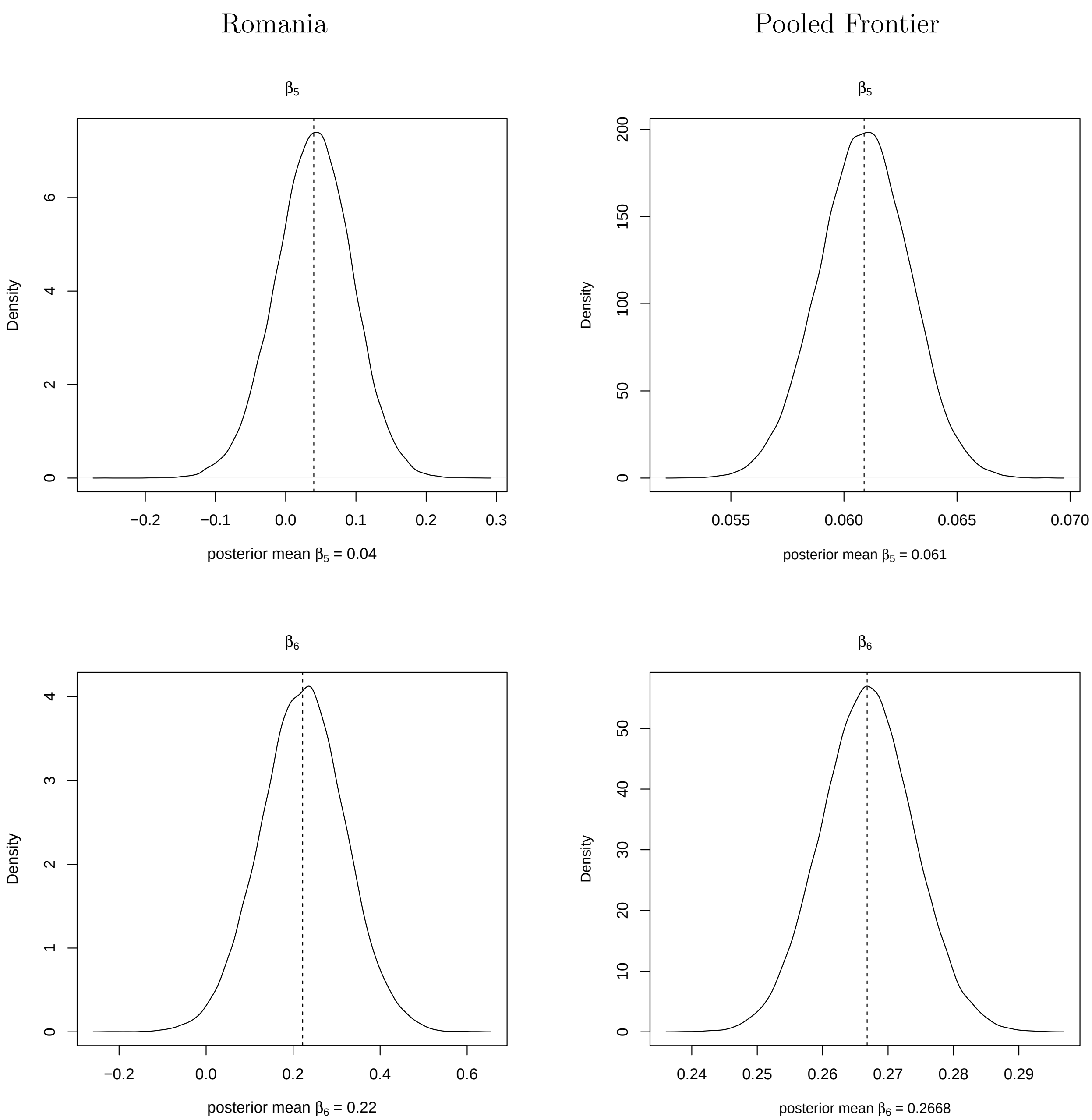


Figure 5.6: Posterior Marginal Densities for Translog Parameters β_5 and β_6.

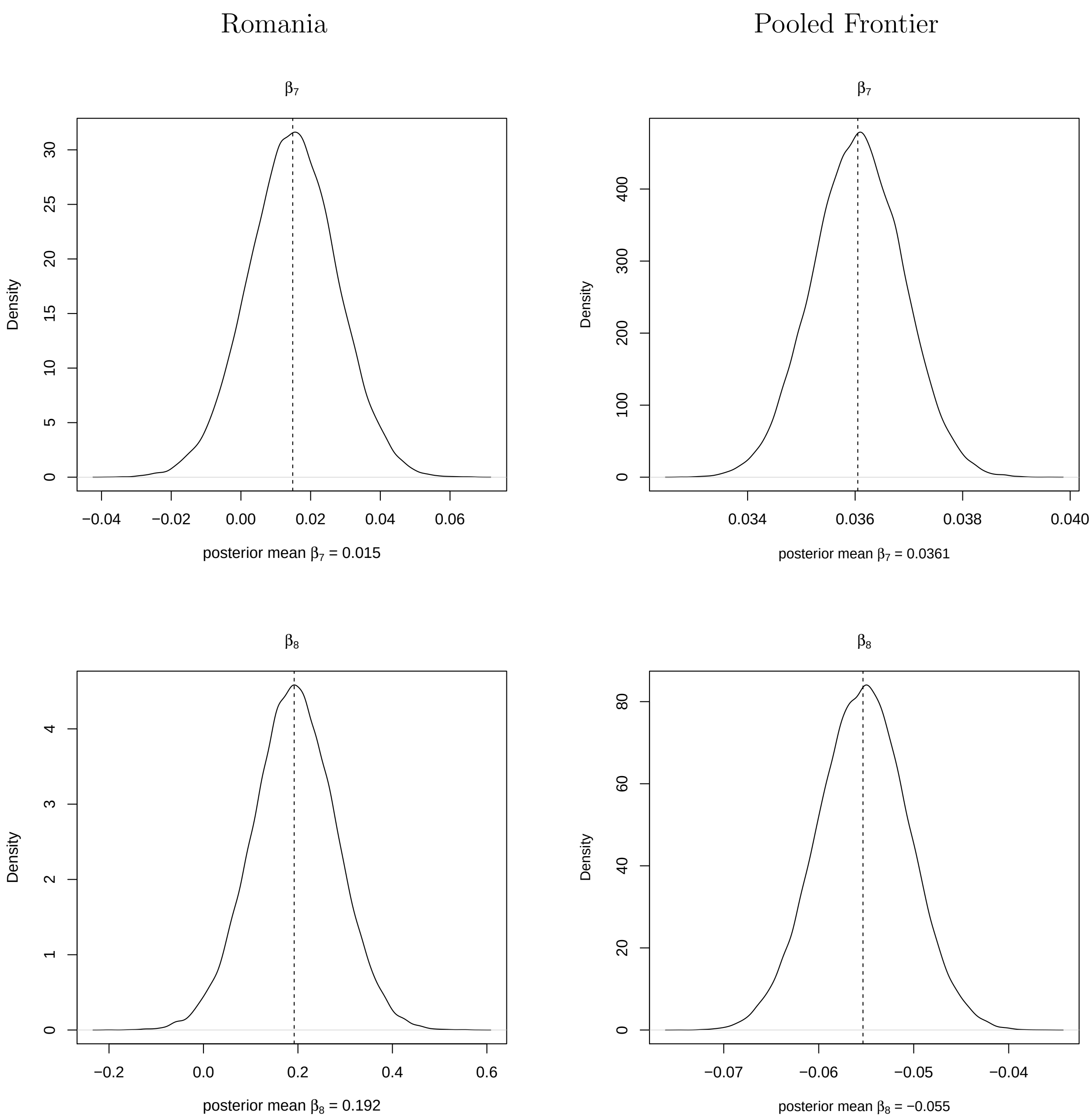


Figure 5.7: Posterior Marginal Densities for Translog Parameters β_7 and β_8.

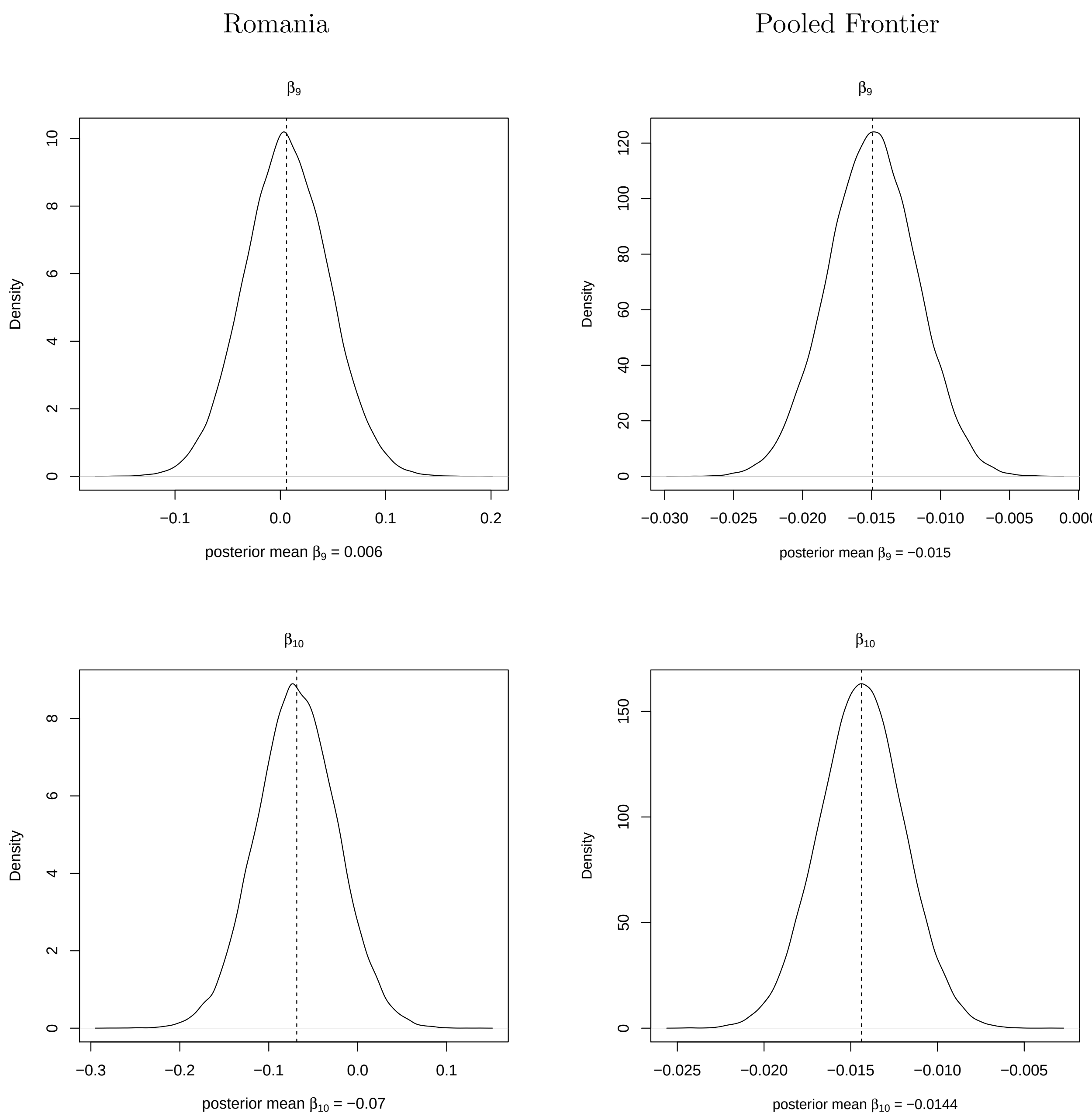
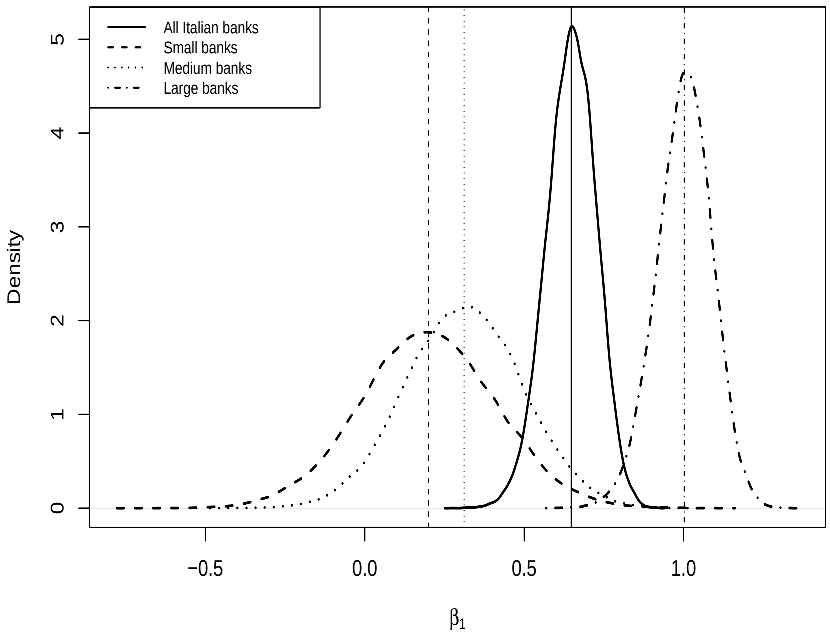


Figure 5.8: Posterior Marginal Densities for Translog Parameters β_9 and β_{10}.

Italy



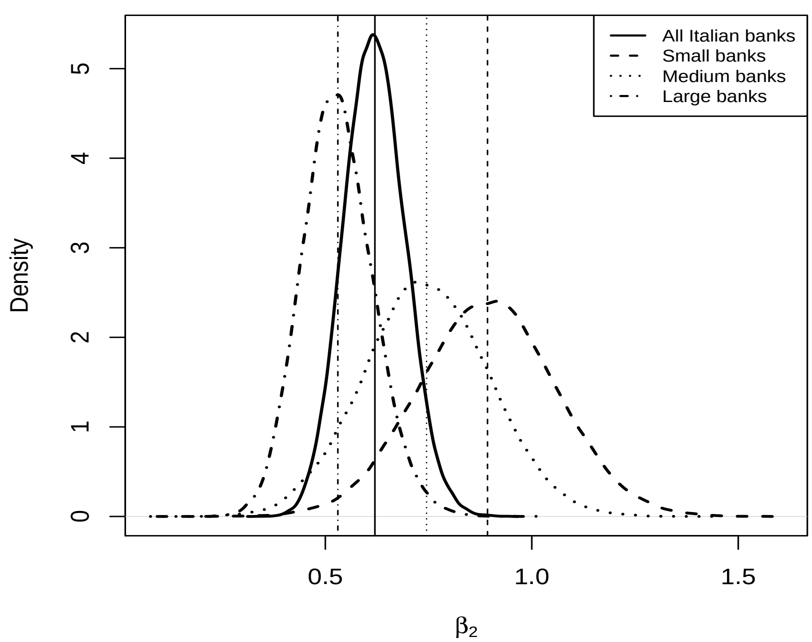
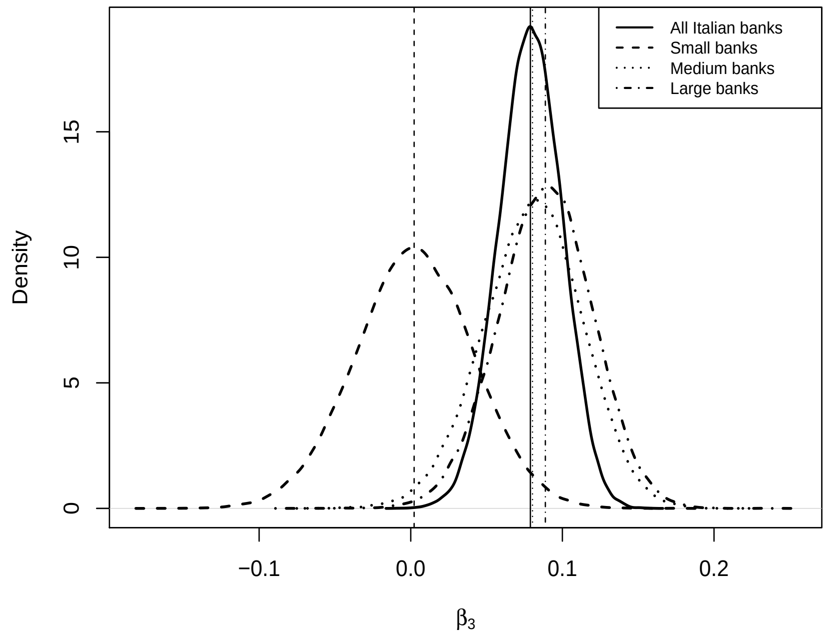


Figure 5.9: Posterior Marginal Densities for Translog Parameters β_1 and β_2 - Italy.

Italy



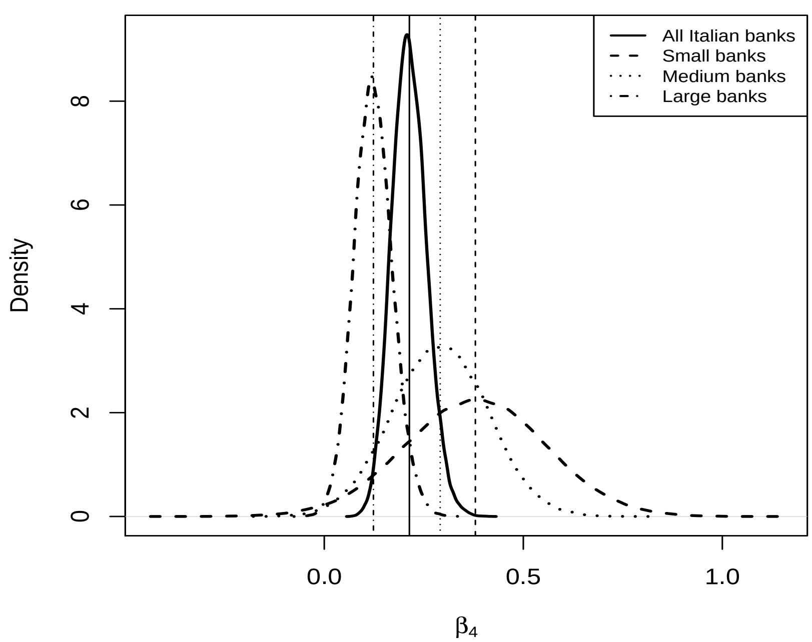


Figure 5.10: Posterior Marginal Densities for Translog Parameters β_3 and β_4 - Italy.

Italy

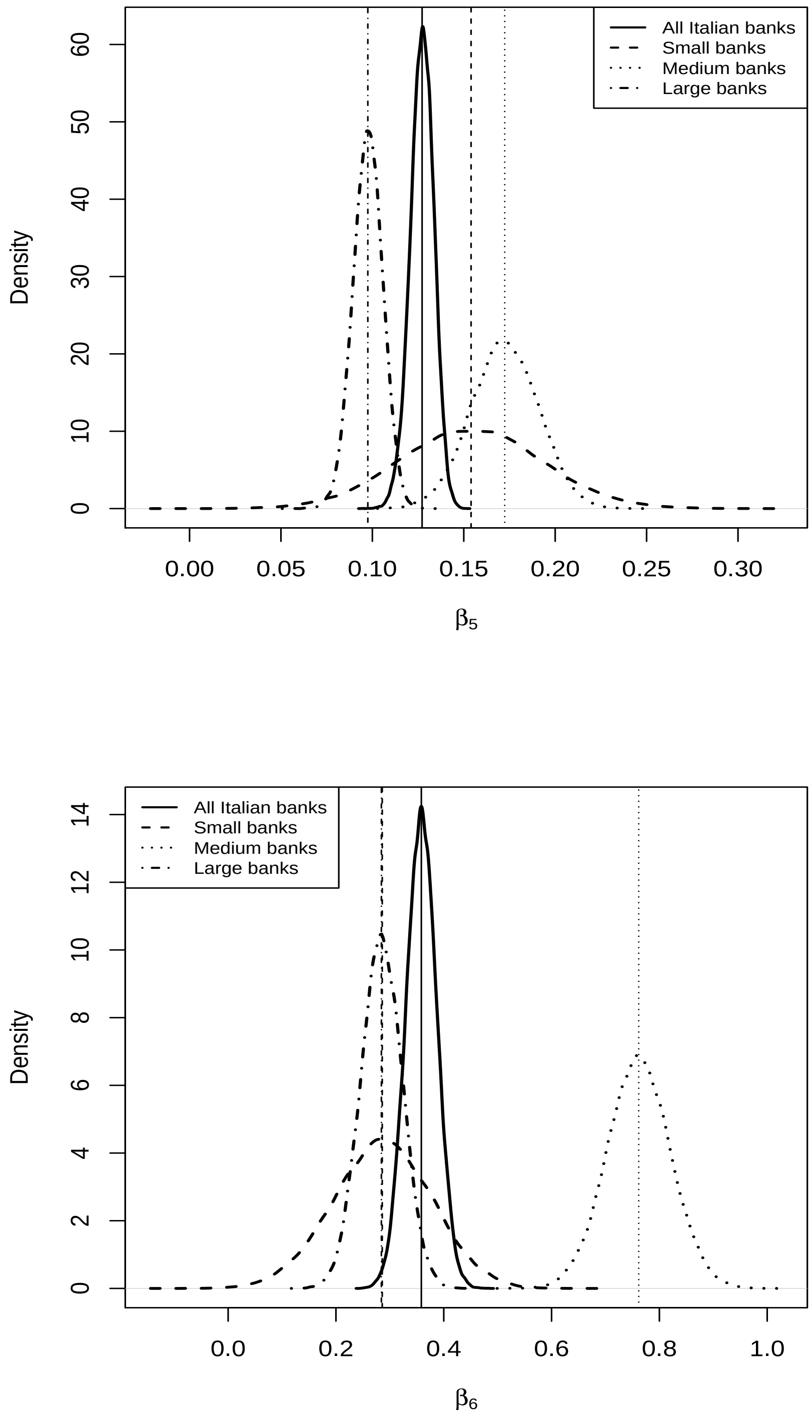
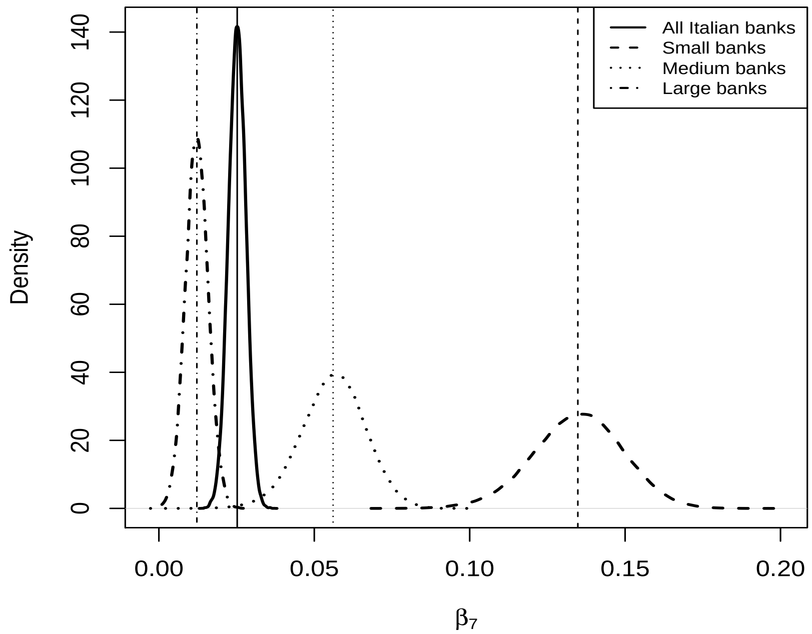


Figure 5.11: Posterior Marginal Densities for Translog Parameters β_5 and β_6 - Italy.



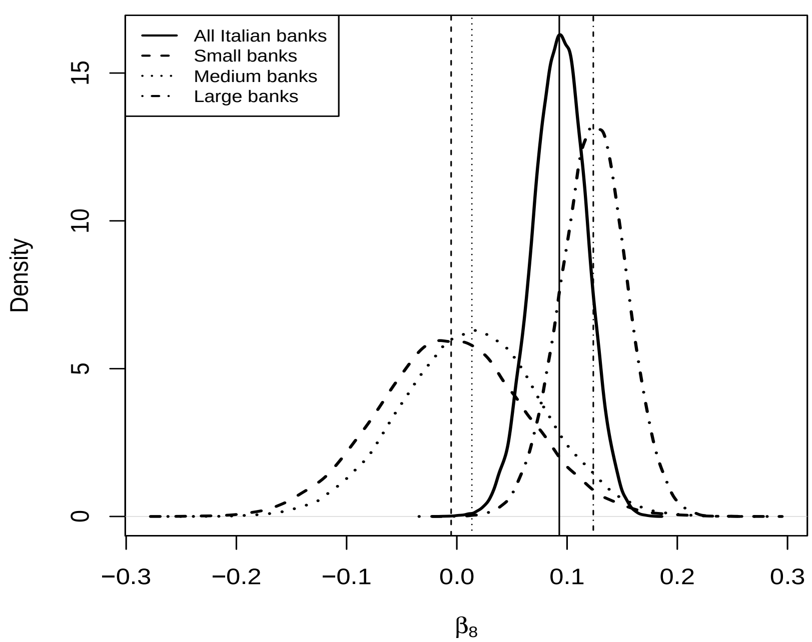
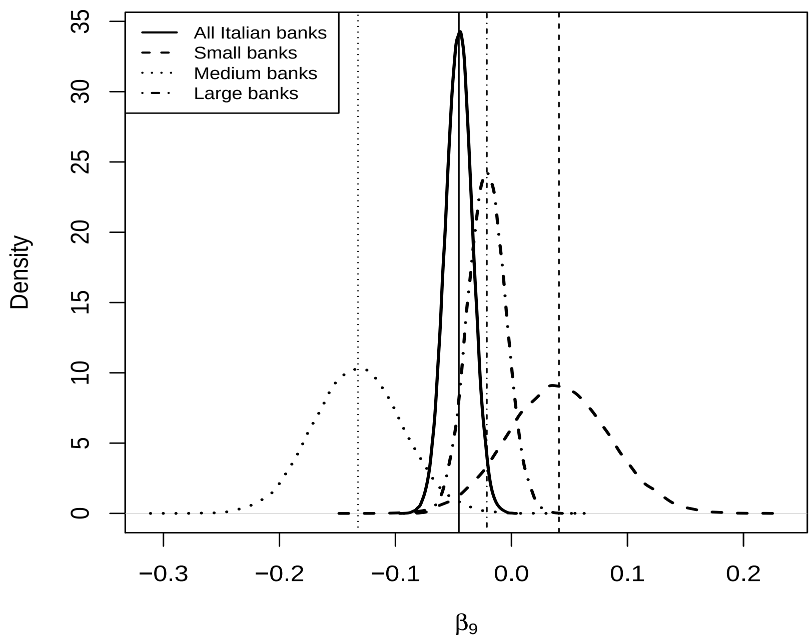


Figure 5.12: Posterior Marginal Densities for Translog Parameters β_7 and β_8 - Italy.

Italy



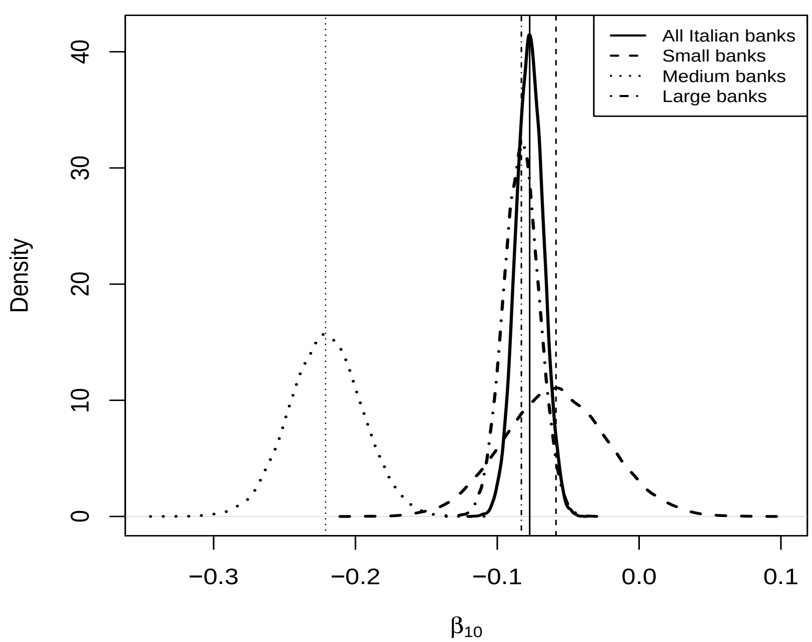


Figure 5.13: Posterior Marginal Densities for Translog Parameters β_9 and β_{10} - Italy.

To complete the analysis of technologies, we evaluate economies of scale[16] for a group of selected banks. For each country, we have picked banks from each of the size types (small, medium and large), all from year 2007, such that their total assets were close to the median value of the respective category and whenever possible, we included not only commercial banks but also cooperative or savings banks.

The economies of scale were calculated not only with respect with the nation's frontier in the case of each bank, but also against the pooled frontier. The results are presented in tables 5.10 through 5.15.

Keeping in mind the rule of thumb that cost scale economies are increasing if the sum of output elasticities of costs is smaller than one, and decreasing if the sum is larger than one, we take a look at the results in the above tables.

The small banks exhibit in general increasing economies of scales against both national frontier(Table 5.10) and pooled frontier (Table 5.11) with a couple of exceptions. The posterior mean for the economies of scale of the Croatian bank (Partner Banka) though less than one (0.9) when computed against the national frontier, has a highest density region that includes one, suggesting that the bank is facing close to constant returns. The Swedish banks (Södra Hestra Sparbank and Vimmerby Sparbank AB) are in a similar situation as the highest density regions for the economies of scale include one even though the posterior means are slightly higher than one (1.04 and respectively 1.10). If the banks from the two countries were to switch to the pooled frontier, there is potential for increasing savings by expanding output.

The highest cost reduction by increasing output on the domestic market would be enjoyed by the French bank (Bank Pouyanne) for which the economies of scale against the national frontier have a posterior mean of 2.37 and while against the pooled frontier the value goes down significantly (1.23), it still remains greater than one.

[16]see Appendix 2 for formula derivations.

Table 5.10: Economies of Scale◊ for Selected Banks (Small): Posterior Means, Standard Deviation, and 90% H.D.R.*

Bank name	Country	Specialization	Total assets	Post. mean	Post. S.D.	*H.D.R.**
Partner Banka dd	HR	Commercial Bank	252.39	0.90	0.13	[0.72 , 1.14]
Lollands Bank	DK	Commercial Bank	311.47	1.56	0.12	[1.38 , 1.77]
Sparekassen i Skals	DK	Savings Bank	269.60	1.45	0.12	[1.26 , 1.67]
Banque Pouyanne	FR	Commercial Bank	301.49	2.37	0.24	[2.02 , 2.80]
Volksbank Sandhofen eG	DE	Cooperative Bank	301.63	1.38	0.02	[1.35 , 1.41]
Sparkasse Froendenberg	DE	Savings Bank	309.73	1.46	0.02	[1.42 , 1.50]
Bankhaus Ludwig Sperrer	DE	Commercial Bank	289.56	1.37	0.01	[1.35 , 1.40]
Banca di Credito Cooperativo di Nettuno	IT	Cooperative Bank	258.94	1.17	0.04	[1.11 , 1.23]
Romanian International Bank SA	RO	Commercial Bank	202.80	1.57	0.52	[1.08 , 2.35]
Cacanska Banka AD, Cacak	RS	Commercial Bank	260.62	1.94	0.66	[1.26 , 2.99]
Södra Hestra Sparbank	SE	Savings Bank	257.34	1.04	0.05	[0.96 , 1.13]
Vimmerby Sparbank AB	SE	Commercial Bank	181.49	1.10	0.08	[0.99 , 1.24]
GRB Glarner Regionalbank	CH	Commercial Bank	296.76	1.54	0.09	[1.41 , 1.69]
Reliance Bank Limited	UK	Commercial Bank	368.12	1.67	0.13	[1.47 , 1.89]

Notes: ◊ Based on national frontiers (M1).
∗ Highest Density Region.
Posterior moments are computed based on 50,000 points generated from the Gibbs sampling algorithm. The end points of the 90% confidence region are the 5^{th} and the 95^{th} percentiles of the posterior marginal densities.

Table 5.11: Economies of Scale$^{\diamond}$ for Selected Banks (Small): Posterior Means, Standard Deviation, and 90% H.D.R.*

Bank name	Country	Specialization	Total assets	Post. mean	Post. S.D.	*H.D.R.**
Partner Banka dd	HR	Commercial Bank	252.39	1.28	0.01	[1.26 , 1.30]
Lollands Bank	DK	Commercial Bank	311.47	1.38	0.01	[1.36 , 1.40]
Sparekassen i Skals	DK	Savings Bank	269.60	1.46	0.02	[1.44 , 1.49]
Banque Pouyanne	FR	Commercial Bank	301.49	1.23	0.01	[1.20 , 1.25]
Volksbank Sandhofen eG	DE	Cooperative Bank	301.63	1.14	0.01	[1.12 , 1.16]
Sparkasse Froendenberg	DE	Savings Bank	309.73	1.06	0.01	[1.04 , 1.08]
Bankhaus Ludwig Sperrer	DE	Commercial Bank	289.56	1.16	0.01	[1.14 , 1.17]
Banca di Credito Cooperativo di Nettuno	IT	Cooperative Bank	258.94	1.49	0.02	[1.46 , 1.52]
Romanian International Bank SA	RO	Commercial Bank	202.80	1.67	0.06	[1.58 , 1.76]
Cacanska Banka AD, Cacak	RS	Commercial Bank	260.62	1.59	0.04	[1.53 , 1.66]
Södra Hestra Sparbank	SE	Savings Bank	257.34	1.41	0.02	[1.39 , 1.44]
Vimmerby Sparbank AB	SE	Commercial Bank	181.49	1.54	0.02	[1.50 , 1.57]
GRB Glarner Regionalbank	CH	Commercial Bank	296.76	1.43	0.02	[1.40 , 1.46]
Reliance Bank Limited	UK	Commercial Bank	368.12	1.25	0.01	[1.23 , 1.27]

Notes: $\diamond$ Based on the pooled frontier (M1).
$*$ Highest Density Region.
Posterior moments are computed based on 50,000 points generated from the Gibbs sampling algorithm. The end points of the 90% confidence region are the 5^{th} and the 95^{th} percentiles of the posterior marginal densities.

Table 5.12: Economies of Scale$^{\diamond}$ for Selected Banks (Medium): Posterior Means, Standard Deviation, and 90% H.D.R.*

Bank name	Country	Specialization	Total assets	Post. mean	Post. S.D.	*H.D.R.**
Medimurska banka dd	HR	Commercial Bank	534.82	1.05	0.12	[0.88 , 1.26]
Froes Herreds Sparekasse	DK	Savings Bank	691.59	1.56	0.11	[1.39 , 1.75]
Morsoe Bank	DK	Commercial Bank	714.60	2.08	0.30	[1.67 , 2.64]
Banque Chalus	FR	Commercial Bank	760.19	1.18	0.04	[1.11 , 1.26]
Raiffeisenbank Straubing eG	DE	Cooperative Bank	702.64	1.45	0.02	[1.42 , 1.48]
Sparkasse Mecklenburg-Strelitz	DE	Savings Bank	722.36	1.48	0.03	[1.44 , 1.52]
Frankfurter Bankgesellschaft AG	DE	Commercial Bank	562.49	1.59	0.03	[1.55 , 1.63]
Cassa rurale di Tuenno	IT	Cooperative Bank	680.70	1.11	0.03	[1.06 , 1.16]
Intesa Sanpaolo Romania SA	RO	Commercial Bank	729.28	1.95	0.56	[1.34 , 2.91]
Volksbank ad	RS	Commercial Bank	986.23	1.74	0.88	[1.18 , 2.68]
Postna Banka Slovenije dd	SI	Commercial Bank	921.97	0.76	0.36	[0.52 , 1.12]
Sparbanken Lidköping AB	SE	Commercial Bank	664.95	0.54	0.05	[0.47 , 0.63]
Roslagens Sparbank Roslagsbanken	SE	Savings Bank	683.14	0.78	0.05	[0.71 , 0.86]
Alternative Bank ABS	CH	Commercial Bank	686.45	1.99	0.20	[1.70 , 2.36]
Turkish Bank A.S.	TR	Commercial Bank	650.28	1.56	0.27	[1.20 , 2.05]
Arbuthnot Latham & Co. Ltd.	UK	Commercial Bank	619.52	1.76	0.19	[1.49 , 2.09]

Notes: $\diamond$ Based on national frontiers (M1).
$*$ Highest Density Region.
Posterior moments are computed based on 50,000 points generated from the Gibbs sampling algorithm. The end points of the 90% confidence region are the 5^{th} and the 95^{th} percentiles of the posterior marginal densities.

Table 5.13: Economies of Scale$^{\diamond}$ for Selected Banks (Medium): Posterior Means, Standard Deviation, and 90% H.D.R.*

Bank name	Country	Specialization	Total assets	Post. mean	Post. S.D.	*H.D.R.**
Medimurska banka dd	HR	Commercial Bank	534.82	1.20	0.01	[1.18 , 1.22]
Froes Herreds Sparekasse	DK	Savings Bank	691.59	1.33	0.01	[1.31 , 1.35]
Morsoe Bank	DK	Commercial Bank	714.60	1.26	0.01	[1.24 , 1.28]
Banque Chalus	FR	Commercial Bank	760.19	1.34	0.01	[1.32 , 1.36]
Raiffeisenbank Straubing eG	DE	Cooperative Bank	702.64	1.14	0.01	[1.12 , 1.16]
Sparkasse Mecklenburg-Strelitz	DE	Savings Bank	722.36	1.02	0.01	[1.01 , 1.04]
Frankfurter Bankgesellschaft AG	DE	Commercial Bank	562.49	1.22	0.01	[1.20 , 1.24]
Cassa rurale di Tuenno	IT	Cooperative Bank	680.70	1.28	0.01	[1.26 , 1.30]
Intesa Sanpaolo Romania SA	RO	Commercial Bank	729.28	1.24	0.02	[1.21 , 1.27]
Volksbank ad	RS	Commercial Bank	986.23	1.63	0.05	[1.55 , 1.71]
Postna Banka Slovenije dd	SI	Commercial Bank	921.97	1.01	0.01	[0.99 , 1.03]
Sparbanken Lidköping AB	SE	Commercial Bank	664.95	1.66	0.02	[1.62 , 1.70]
Roslagens Sparbank Roslagsbanken	SE	Savings Bank	683.14	1.63	0.03	[1.59 , 1.68]
Alternative Bank ABS	CH	Commercial Bank	686.45	1.30	0.02	[1.27 , 1.33]
Turkish Bank A.S.	TR	Commercial Bank	650.28	1.37	0.03	[1.32 , 1.41]
Arbuthnot Latham & Co. Ltd.	UK	Commercial Bank	619.52	1.19	0.01	[1.17 , 1.21]

Notes: $\diamond$ Based on the pooled frontier (M1).
$*$ Highest Density Region.
Posterior moments are computed based on 50,000 points generated from the Gibbs sampling algorithm. The end points of the 90% confidence region are the 5^{th} and the 95^{th} percentiles of the posterior marginal densities.

Table 5.14: Economies of Scale$^{\diamond}$ for Selected Banks (Large): Posterior Means, Standard Deviation, and 90% H.D.R.*

Bank name	Country	Specialization	Total assets	Post. mean	Post. S.D.	*H.D.R.**
Hrvatska Postanska Bank DD	HR	Commercial	2920.69	1.06	0.24	[0.78 , 1.49]
Skandinaviska Enskilda Banken	DK	Commercial	2770.29	0.95	0.10	[0.80 , 1.12]
Banque Populaire des Alpes	FR	Cooperative	10741.06	1.26	0.09	[1.12 , 1.41]
Société Bordelaise de Crédit Ind. et Comm.	FR	Commercial	8894.45	0.86	0.07	[0.75 , 0.98]
Kreissparkasse Limburg	DE	Savings	2119.09	1.43	0.02	[1.39 , 1.47]
Hamburger Volksbank eG	DE	Cooperative	2134.40	1.49	0.02	[1.46 , 1.53]
Thüringer Aufbaubank	DE	Commercial	2660.68	1.20	0.01	[1.18 , 1.23]
Banca Padovana Credito Cooperativo SC	IT	Cooperative	3232.59	1.04	0.02	[1.00 , 1.07]
Cassa di risparmio di Alessandria SpA	IT	Savings	3381.27	0.94	0.02	[0.91 , 0.98]
Banca Monte Parma SpA	IT	Commercial	3477.11	0.98	0.02	[0.95 , 1.02]
Staalbankiers NV	NL	Commercial	4380.10	2.57	0.82	[1.77 , 3.81]
Bank BPH SA	PL	Commercial	5347.76	1.10	0.19	[0.85 , 1.45]
Banca Romaneasca SA	RO	Commercial	2776.87	1.60	0.66	[1.06 , 2.47]
AIK Banka ad Nis	RS	Commercial	1457.16	1.82	0.85	[1.15 , 2.92]
Gorenjska Banka d.d. Kranj	SI	Commercial	2551.01	0.85	0.27	[0.58 , 1.26]
Färs & Frosta Sparbank AB	SE	Commercial	1702.99	1.35	0.11	[1.18 , 1.54]
ABN Amro Bank (Schweiz) AG	CH	Commercial	3294.00	2.43	0.23	[2.10 , 2.83]
Anadolubank A.S.	TR	Commercial	2702.80	1.67	0.41	[1.20 , 2.37]
JP Morgan International Bank Ltd	UK	Commercial	7361.90	1.58	0.18	[1.32 , 1.91]

Notes: $\diamond$ Based on national frontiers (M1).
$*$ Highest Density Region.
Posterior moments are computed based on 50,000 points generated from the Gibbs sampling algorithm. The end points of the 90% confidence region are the 5^{th} and the 95^{th} percentiles of the posterior marginal densities.

Table 5.15: Economies of Scale$^{\diamond}$ for Selected Banks (Large): Posterior Means, Standard Deviation, and 90% H.D.R.*

Bank name	Country	Specialization	Total assets	Post. mean	Post. S.D.	*H.D.R.**
Hrvatska Postanska Bank DD	HR	Commercial	2920.69	1.11	0.01	[1.09 , 1.13]
Skandinaviska Enskilda Banken A/S	DK	Commercial	2770.29	1.92	0.04	[1.86 , 1.99]
Banque Populaire des Alpes	FR	Cooperative	10741.06	1.53	0.02	[1.49 , 1.57]
Société Bordelaise de Crédit Ind. et Comm.	FR	Commercial	8894.45	1.41	0.03	[1.36 , 1.45]
Kreissparkasse Limburg	DE	Savings	2119.09	1.02	0.01	[1.00 , 1.03]
Hamburger Volksbank eG	DE	Cooperative	2134.40	1.19	0.01	[1.17 , 1.21]
Thüringer Aufbaubank	DE	Commercial	2660.68	1.05	0.01	[1.03 , 1.07]
Banca Padovana Credito Cooperativo SC	IT	Cooperative	3232.59	1.20	0.01	[1.18 , 1.21]
Cassa di risparmio di Alessandria SpA	IT	Savings	3381.27	1.27	0.01	[1.25 , 1.29]
Banca Monte Parma SpA	IT	Commercial	3477.11	1.15	0.01	[1.14 , 1.17]
Staalbankiers NV	NL	Commercial	4380.10	1.29	0.01	[1.27 , 1.31]
Bank BPH SA	PL	Commercial	5347.76	1.27	0.01	[1.25 , 1.29]
Banca Romaneasca S.A.	RO	Commercial	2776.87	1.32	0.02	[1.29 , 1.36]
AIK Banka ad Nis	RS	Commercial	1457.16	1.48	0.03	[1.42 , 1.54]
Gorenjska Banka d.d. Kranj	SI	Commercial	2551.01	1.30	0.01	[1.28 , 1.33]
Färs & Frosta Sparbank AB	SE	Commercial	1702.99	1.41	0.02	[1.38 , 1.44]
ABN Amro Bank (Schweiz) AG	CH	Commercial	3294.00	1.41	0.01	[1.38 , 1.43]
Anadolubank A.S.	TR	Commercial	2702.80	1.10	0.01	[1.07 , 1.12]
JP Morgan International Bank Ltd	UK	Commercial	7361.90	1.37	0.02	[1.34 , 1.41]

Notes: $\diamond$ Based on the pooled frontier (M1).
$*$ Highest Density Region.
Posterior moments are computed based on 50,000 points generated from the Gibbs sampling algorithm. The end points of the 90% confidence region are the 5^{th} and the 95^{th} percentiles of the posterior marginal densities.

General findings for the pooled technology implies lower economies of scale values for 9 out the 14 banks. Only the Italian, Swedish and Croatian banks appear closer to constant returns against the pooled frontier while the Danish savings bank maintains the same value of the economies of scale.

The economies of scale for the medium banks are presented in tables 5.12 (for the domestic market) and 5.13 (for the pooled frontier). Against the national frontier, the Swedish (Sparbanken Lidköping AB and Roslagens Sparbank Roslagsbanken) and the Slovenian (Postna Banka Slovenije dd) banks have very low values for the economies of scales' posterior means (0.54, 0.78 and 0.76). Nevertheless, only the highest density regions for the Swedish banks confirm the presence of diseconomies of scale while the highest density region for the Slovenian bank includes one, suggesting that the bank might actually face constant returns. When computed against the pooled frontier, while the Slovenian banks remains in the region of constant returns, the Swedish banks exhibit increasing returns, the posterior means for economies of scale increasing to 1.66 (Sparbanken Lidköping AB) and 1.63 (Roslagens Sparbank Roslagsbanken). The Croatian bank (Medimurska banka dd) has a similar situation: with the domestic technology, there is no potential for decreasing cost by increasing the output (the posterior mean of the economies of scale is 1.05 and the highest density region includes 1), but by switching to the pooled frontier's technology, the costs can be reduced. The Italian and French banks register increasing scale economies domestically, but their savings would improve on the pooled frontier. For all the other chosen banks, the cost scale economies are greater than one on both cases, but they fare better against the national frontier.

When it comes to the large banks, we observe posterior means for the economies of scale lower than one when computed against the national frontier for only five of the selected banks in four countries.

In France, Société Bordelaise de Crédit Industriel et Commercial shows diseconomies of scale with a posterior mean of 0.86, in Slovenia, the computed posterior mean for the economies of scale at Gorenjska Banka d.d. Kranj is 0.85, in Denmark, for Sandkandinaviska Enskilda Banken economies of scale posterior mean is 0.95 while in Italy, Banca Monte Parma with 0.98 and Cassa di risparmio di Alessandria with 0.94 are really close to one. In only two of this cases (Société Bordelaise de Crédit Industriel et Commercial and Cassa di risparmio di Alessandria), the highest density regions do not include one, suggesting that the banks truly exhibit diseconomies of scale. For the other three banks, the highest density regions include one suggesting that they more likely have constant returns. For all the other selected banks, the posterior means of the economies of scales are greater than one, though in the case of the Polish (Bank BPH SA) and Croatian (Hrvatska Postanska Bank DD) banks, the highest density regions are wider (lower number of observations) and include one. The two outlier banks that would enjoy the highest savings by increasing their output are the Dutch (Staalbankiers, 2.57) and the Swiss (ABN Amro Bank Schweiz, 2.43) banks.

When computed against the pooled frontier, the economies of scale for all the large banks are greater than one. This means that the Société Bordelaise de Crédit Industriel et Commercial and Cassa di risparmio di Alessandria are moving from decreasing to increasing cost scale economies as they switch from the national to the pooled technology. Other banks that would benefit from the change in technology are the ones from Croatia, Italy, Poland, Slovenia and Sweden as the posterior means of the scale economies increases for them. For all the other countries, the posterior means of the economies of scale decrease, but still remain greater then one.

Figures 5.14 through 5.27 illustrate the estimated economies of scale for the large banks' group as we draw side by side the posterior marginal densities for each bank based on both the national and pooled frontiers.

While the conditional distributions for the technology parameters are normal, there is no expectation for the economies of scale as a nonlinear function of the β's to have a symmetric posterior marginal density. Nevertheless, the smoothed posterior marginal densities for the large banks' economies of scale are mostly symmetric in the case of the pooled frontier. They are also narrow, having a low variance (as expected from the highest density region column of tables 5.14 and 5.15). Both behaviors are explained by the large number of observations used to estimate the pooled frontier ($N = 13970$, the total number of observations in the dataset). As the countries frontiers are estimated based on a small number of observations (sometimes less than 100, i.e. Poland, Serbia, Turkey), the plots of the posterior marginal densities exhibit asymmetry for the national frontier for most of the countries (with the exception of Italy and Germany, the two countries in the dataset with the most observations).

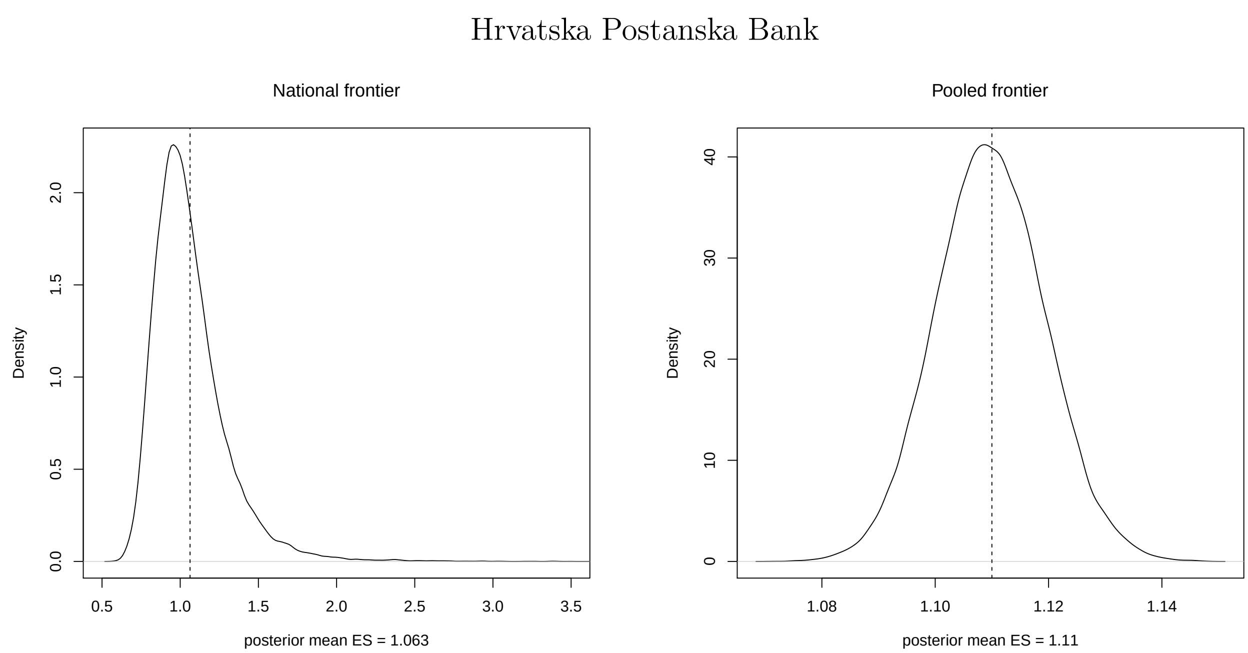


Figure 5.14: Croatia - Posterior Marginal Density for Economies of Scale, Large Bank.

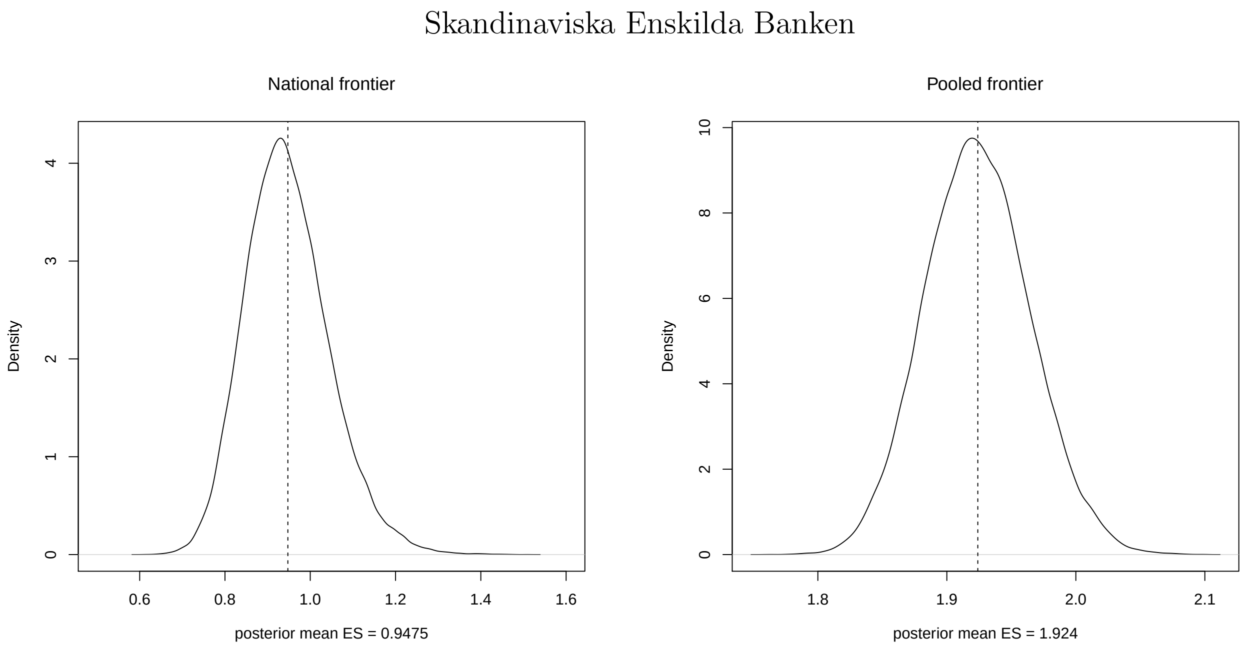


Figure 5.15: Denmark - Posterior Marginal Density for Economies of Scale, Large Bank.

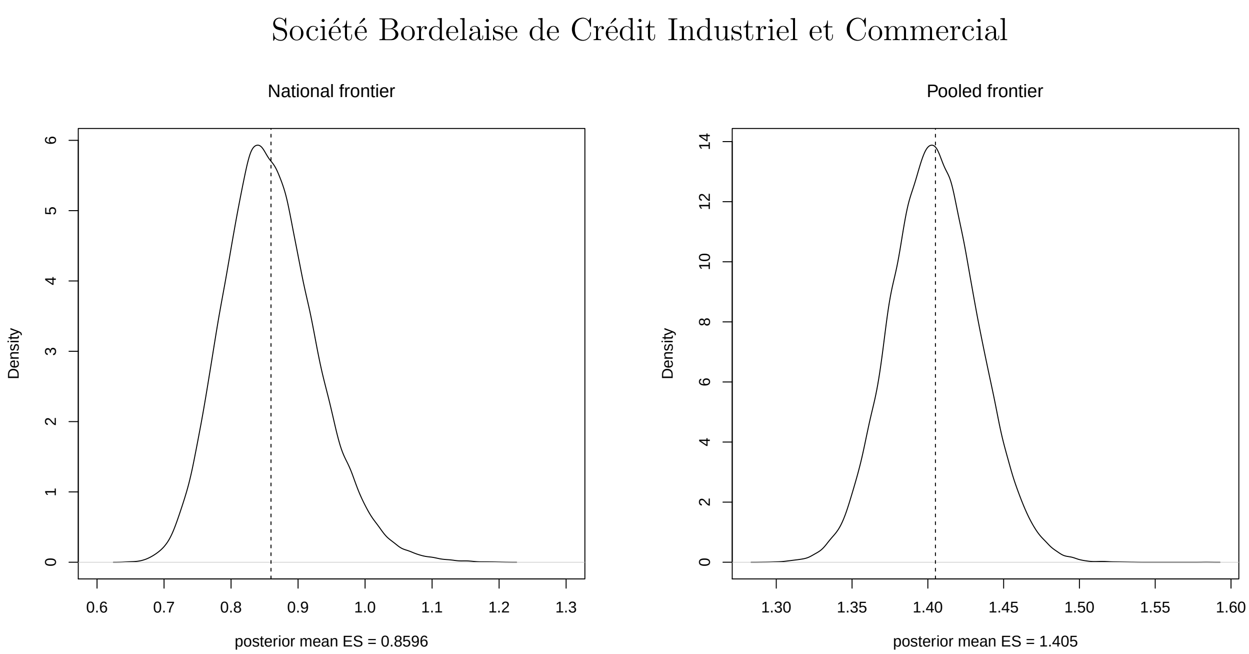


Figure 5.16: France - Posterior Marginal Density for Economies of Scale, Large Bank.

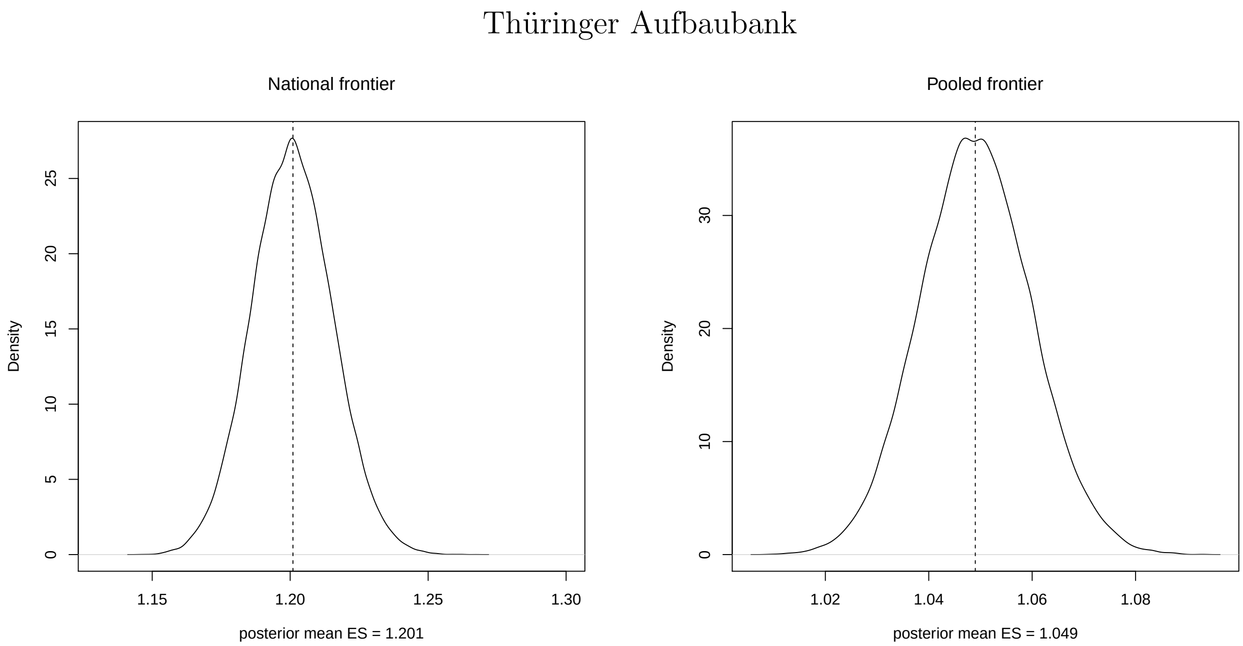


Figure 5.17: Germany - Posterior Marginal Density for Economies of Scale, Large Bank.

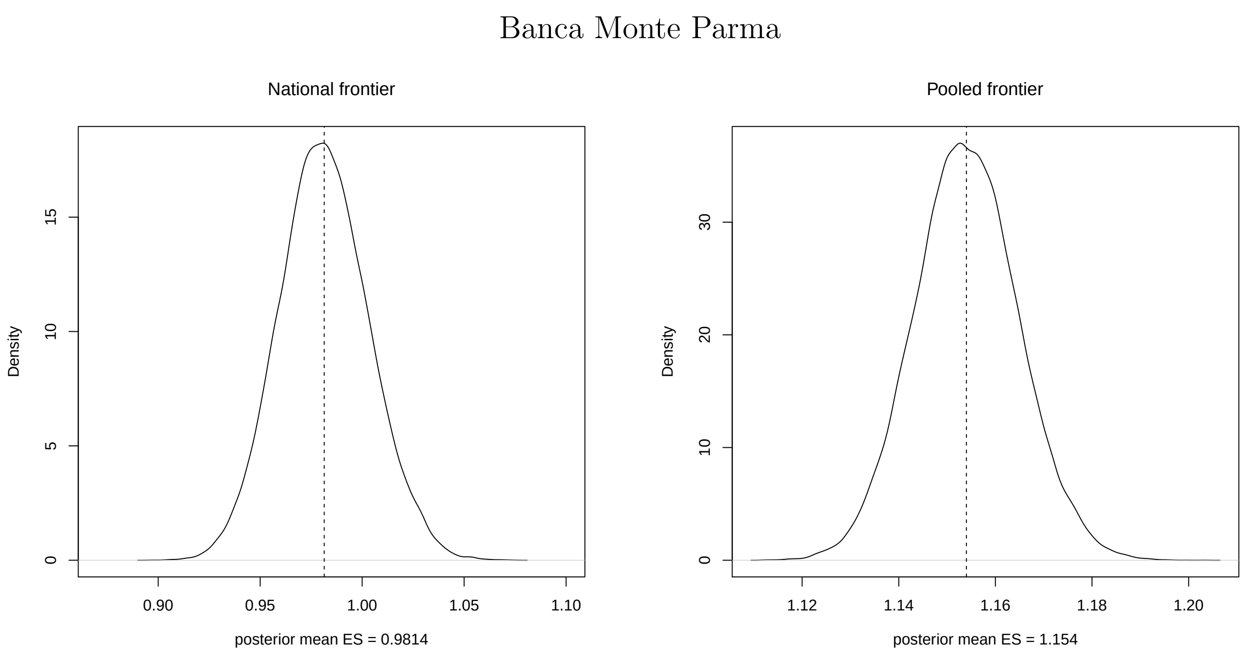


Figure 5.18: Italy - Posterior Marginal Density for Economies of Scale, Large Bank.

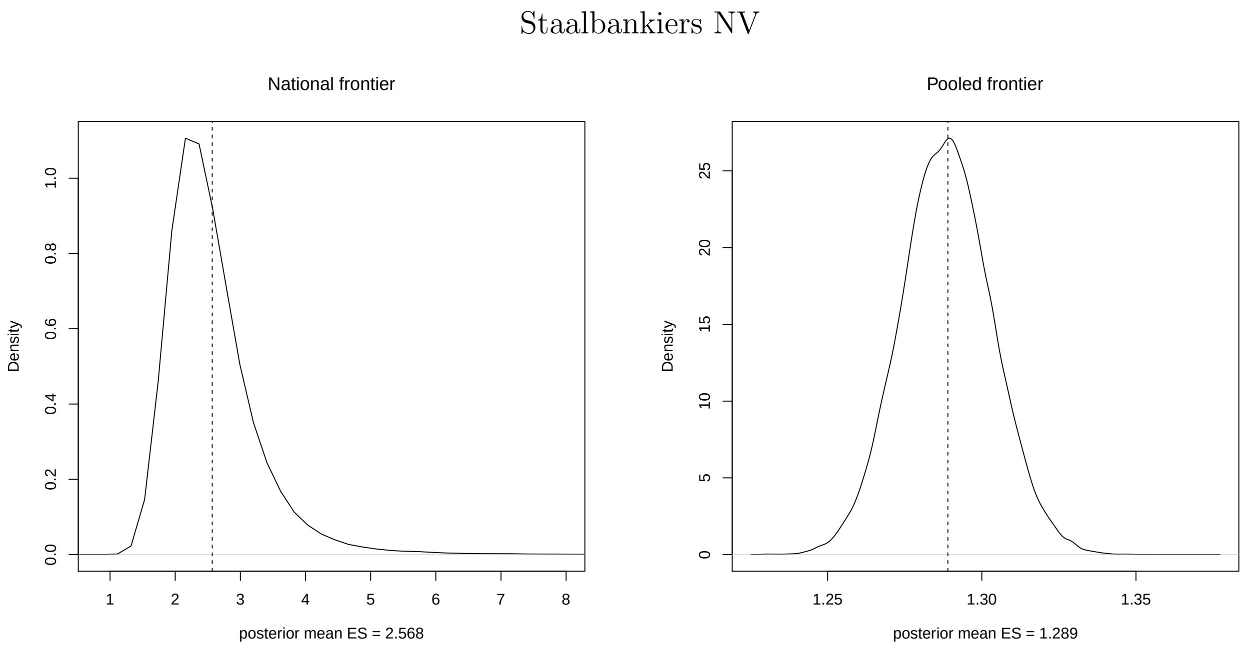


Figure 5.19: Netherlands - Posterior Marginal Density for Economies of Scale, Large Bank.

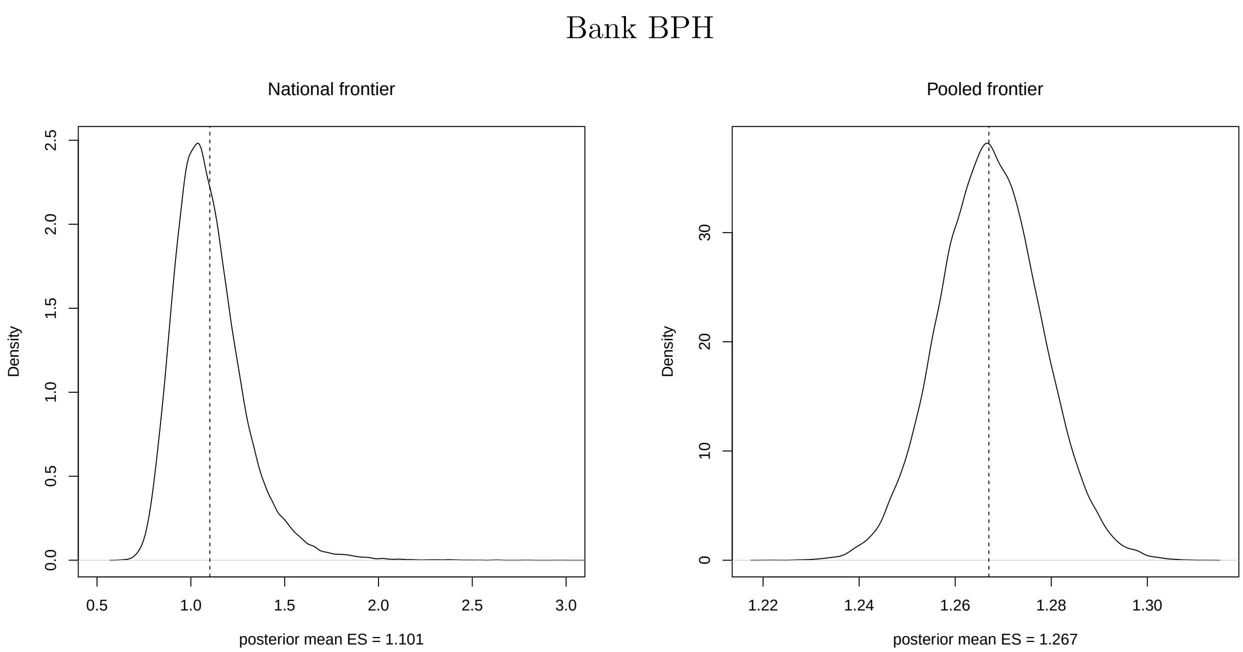


Figure 5.20: Poland - Posterior Marginal Density for Economies of Scale, Large Bank.

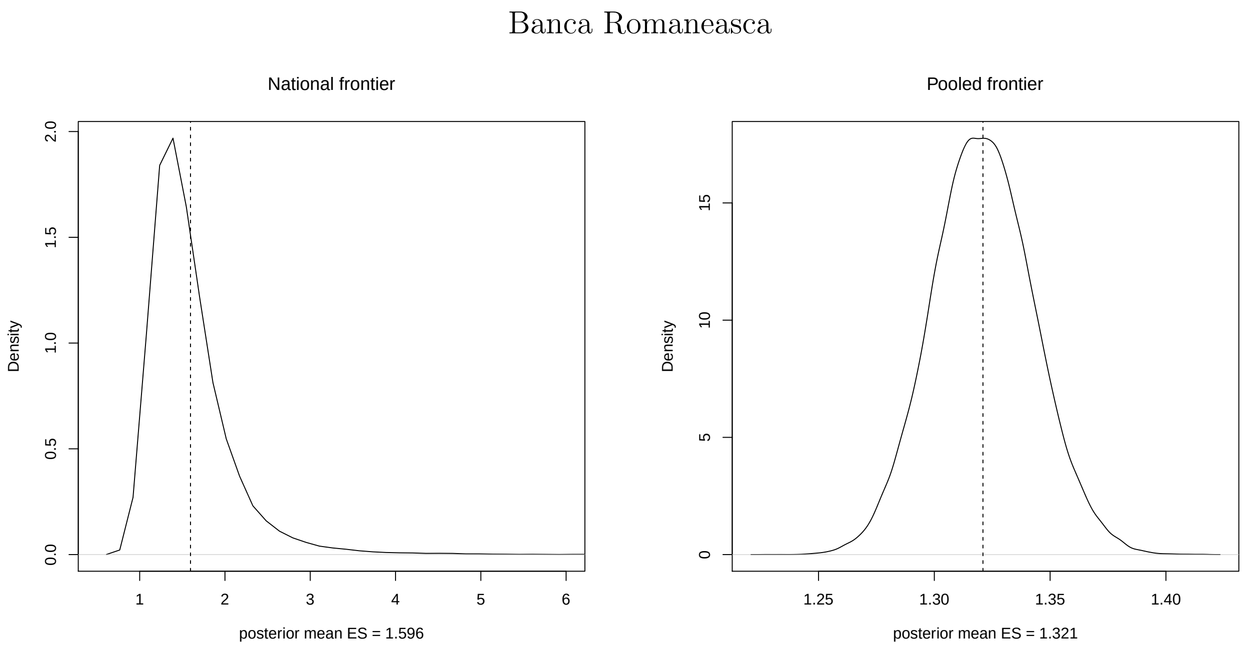


Figure 5.21: Romania - Posterior Marginal Density for Economies of Scale, Large Bank.

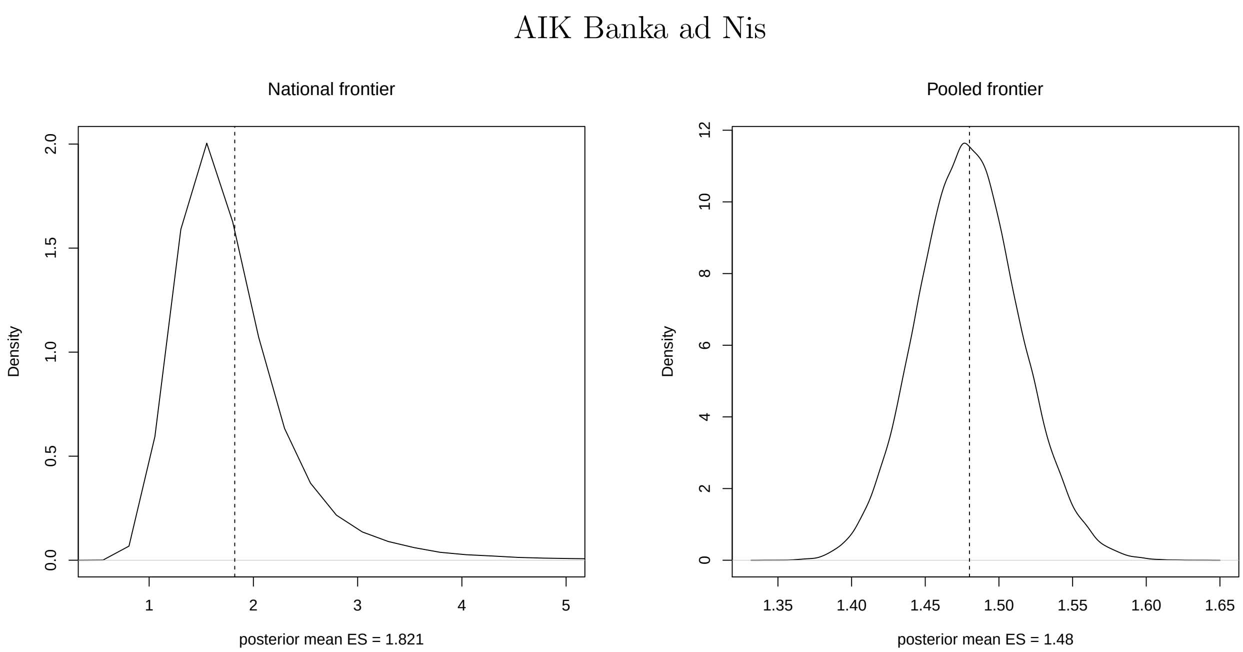


Figure 5.22: Serbia - Posterior Marginal Density for Economies of Scale, Large Bank.

Gorenjska Banka d.d. Kranj

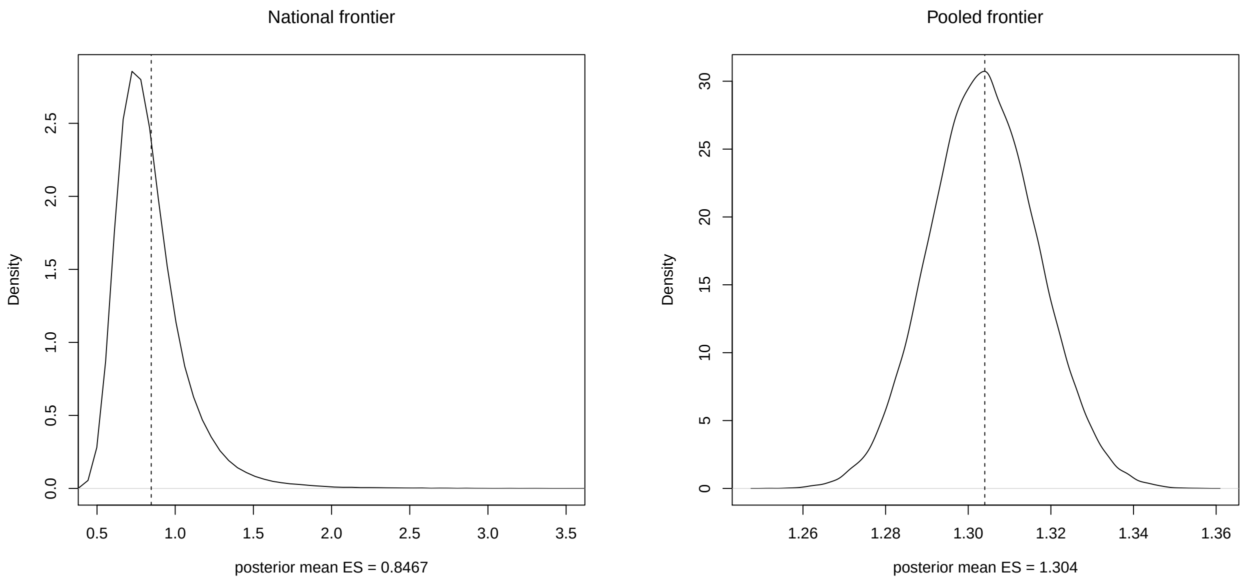


Figure 5.23: Slovenia - Posterior Marginal Density for Economies of Scale, Large Bank.

Färs & Frosta Sparbank AB

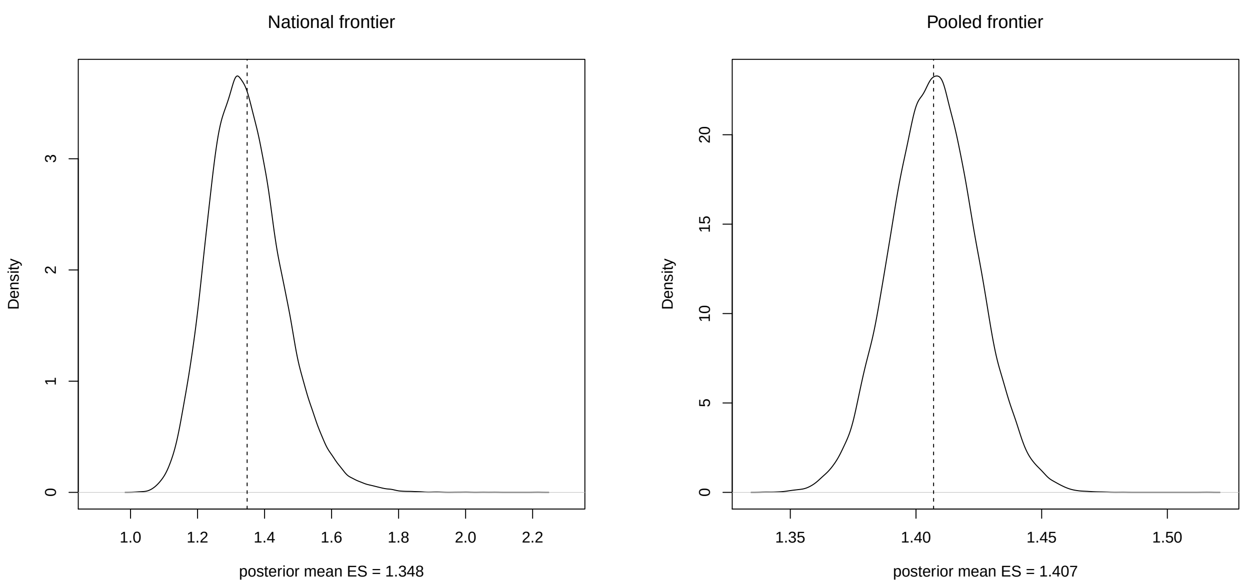


Figure 5.24: Sweden - Posterior Marginal Density for Economies of Scale, Large Bank.

ABN Amro Bank (Schweiz) AG

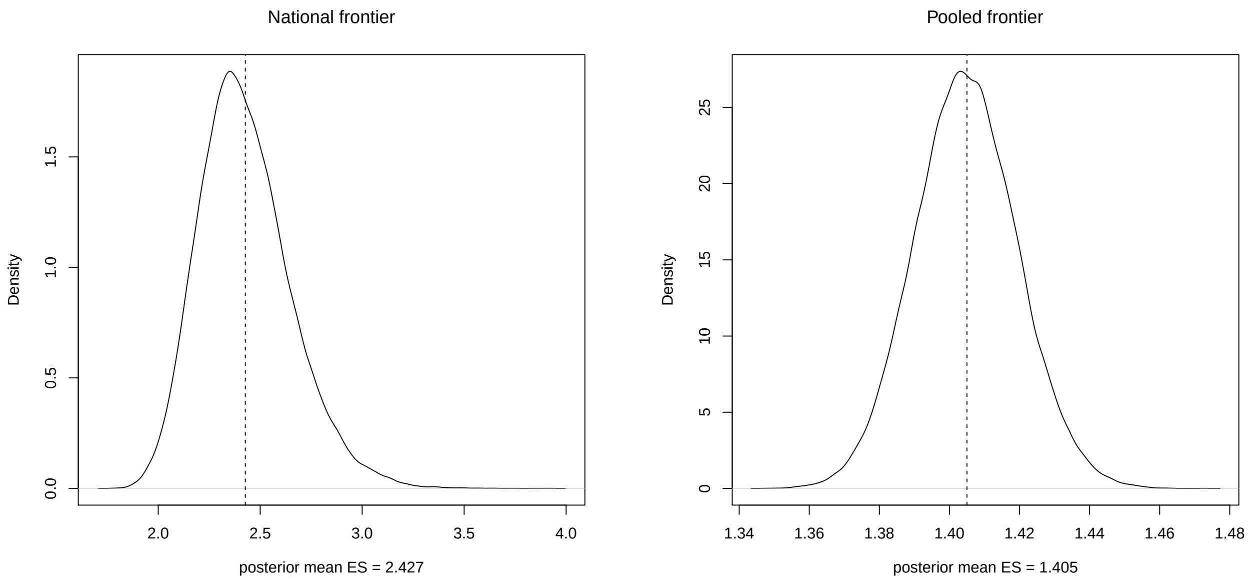


Figure 5.25: Switzerland - Posterior Marginal Density for Economies of Scale, Large Bank.

Anadolubank AS

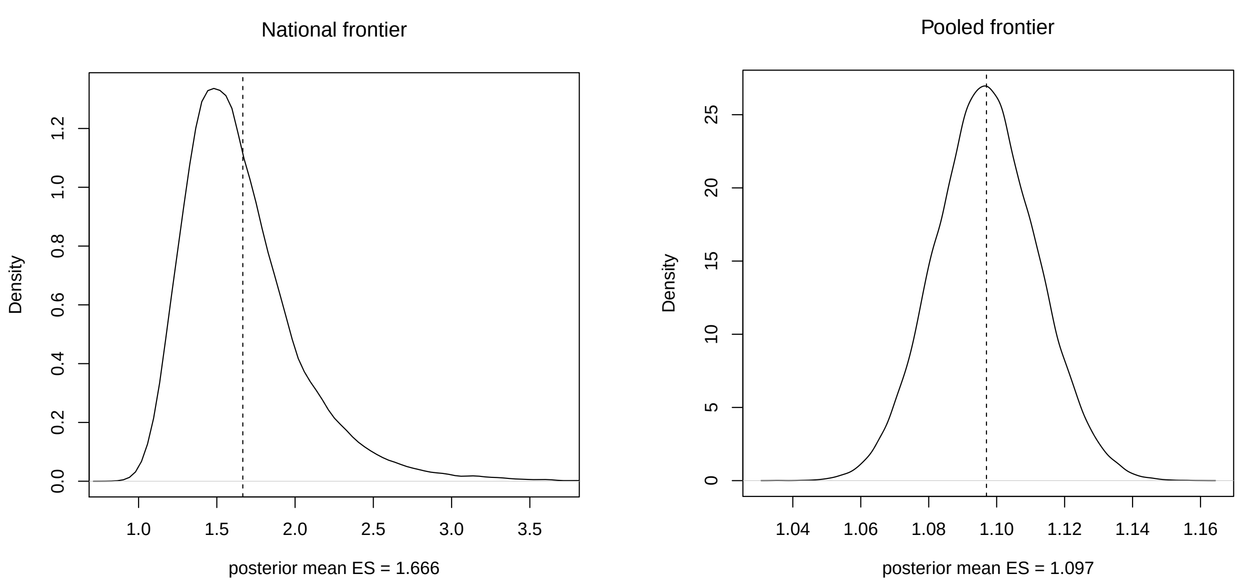


Figure 5.26: Turkey - Posterior Marginal Density for Economies of Scale, Large Bank.

JP Morgan International Bank Ltd

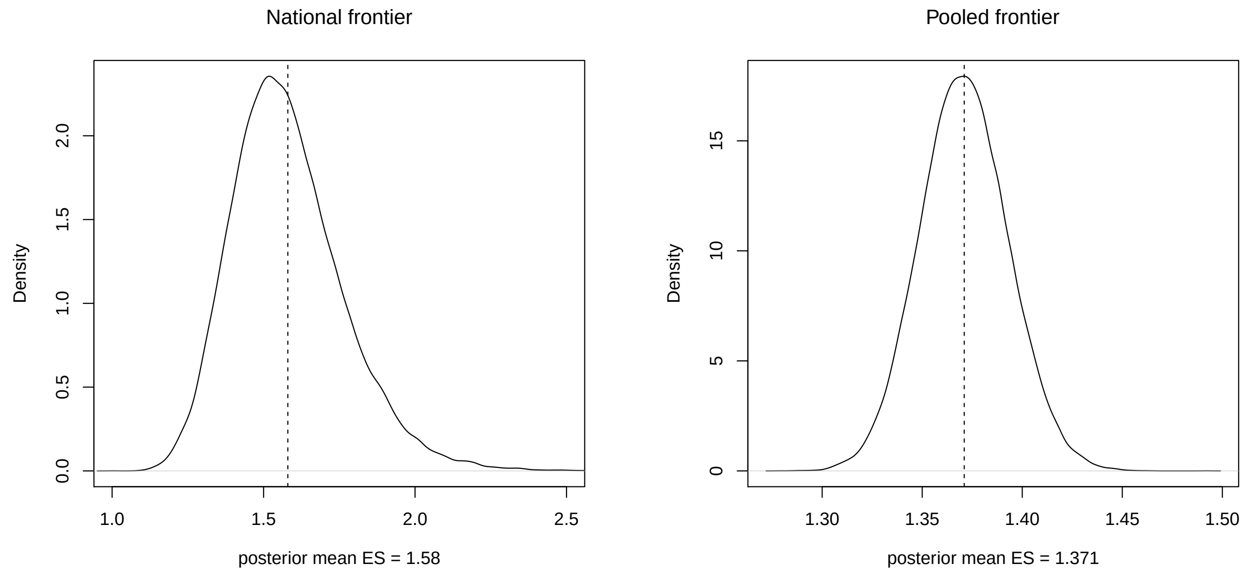


Figure 5.27: United Kingdom - Posterior Marginal Density for Economies of Scale, Large Bank.

In tables 5.16 and 5.18 we record the posterior means and the 90 percent highest posterior density regions for the λ and σ_u^2 variables calculated for the countries of interest, while Table 5.17 contains the associated posterior means of the efficiency scores for each country, their posterior standard deviation and the 5^{th} and 95^{th} quartiles. When computing the posterior means of the efficiency scores, we use the 50,000 sampled values obtained through the Gibbs sample algorithm from the marginal posterior distribution of the λ parameter to calculate $\bar{r} = \mathrm{E}[\exp(-\lambda)|\text{data}]$.

Looking at the overall results for each country, the most efficient banks relative to their own frontier are the ones from Slovenia (with the posterior mean for λ of 0.0851, mean efficiency score of 91.93 percent) and the least efficient ones are the ones from Switzerland (with the posterior mean for λ of 0.5112, mean efficiency score of 59.86 percent) and Serbia (with the posterior mean for λ of 0.5139, mean efficiency score of 60.28 percent).

Table 5.16: λ - Posterior Means and Standard Deviation, 90% H.D.R.*

Countries\Bank size		Obs.	No. banks	λ	Post. S.D.	Q_5	Q_{95}
Pooled frontier	all	13970	2819	0.1989	0.0058	0.1892	0.2084
	small	5305	1479	0.2414	0.0108	0.2236	0.2591
	medium	2881	927	0.2270	0.0113	0.2084	0.2457
	large	5784	1269	0.1971	0.0082	0.1836	0.2108
CROATIA		121	26	0.1090	0.0499	0.0384	0.1989
DENMARK	all	375	78	0.1899	0.0359	0.1326	0.2485
	small	174	51	0.0894	0.0416	0.0345	0.1680
	large	132	39	0.1490	0.0536	0.0542	0.2334
FRANCE	all	527	171	0.4078	0.0333	0.3534	0.4630
	large	452	150	0.3634	0.0306	0.3141	0.4141
GERMANY	all	8668	1471	0.1601	0.0040	0.1536	0.1667
	small	3111	823	0.1821	0.0064	0.1717	0.1928
	medium	2021	562	0.1413	0.0069	0.1299	0.1527
	large	3536	630	0.1564	0.0054	0.1475	0.1653
ITALY	all	1818	561	0.2168	0.0097	0.2011	0.2330
	small	745	287	0.1767	0.0126	0.1563	0.1977
	medium	355	158	0.1528	0.0149	0.1290	0.1776
	large	718	215	0.2516	0.0189	0.2208	0.2829
NETHERLANDS	all	134	36	0.2002	0.1408	0.0424	0.4865
	large	118	33	0.2459	0.1746	0.0417	0.5702
POLAND		93	28	0.0916	0.0469	0.0342	0.1823
ROMANIA		104	23	0.1598	0.0799	0.0457	0.3010
SERBIA		80	25	0.5139	0.1223	0.3099	0.6959
SLOVENIA		84	17	0.0851	0.0426	0.0318	0.1669
SWEDEN	all	344	61	0.1408	0.0459	0.0616	0.2125
	small	235	48	0.1118	0.0449	0.0421	0.1878
SWITZERLAND	all	1188	221	0.5112	0.0291	0.4650	0.5609
	small	749	170	0.4939	0.0303	0.4441	0.5437
	medium	201	69	0.3739	0.0384	0.3133	0.4398
	large	238	44	0.3869	0.0419	0.3180	0.4553
TURKEY		84	18	0.1863	0.0752	0.0577	0.3053
UNITED KINGDOM	all	350	85	0.1653	0.1011	0.0396	0.3591
	small	87	25	0.1556	0.1075	0.0420	0.3729
	large	226	60	0.1583	0.0947	0.0396	0.3357

Notes:* Highest Density Region
Posterior moments are computed based on 50,000 points generated from the Gibbs sampling algorithm.
The end points of the 90% confidence region are the 5^{th} and the 95^{th} percentiles of the marginal densities.
If total assets $\geq$1,000 millions dollars, the bank is large. Banks with total assets between 100 and 500 millions are small. Banks with total assets between 500 and 1,000 millions are of medium size.

Table 5.17: Efficiency Score - Posterior Means and Standard Deviation, 90% H.D.R.*

Countries\Bank size		Obs.	No. banks	$r_j^\dagger$	Post. S.D.	Q_5	Q_{95}
Pooled frontier	all	13970	2819	0.8197	0.0048	0.8119	0.8276
	small	5305	1479	0.7856	0.0085	0.7718	0.7997
	medium	2881	927	0.7970	0.009	0.7821	0.8119
	large	5784	1269	0.8211	0.0068	0.8099	0.8322
CROATIA		121	26	0.8979	0.0442	0.8196	0.9623
DENMARK	all	375	78	0.8276	0.0297	0.7799	0.8758
	small	174	51	0.9153	0.0374	0.8453	0.9661
	large	132	39	0.8628	0.0464	0.7918	0.9473
FRANCE	all	527	171	0.6655	0.0222	0.6294	0.7023
	large	452	150	0.6957	0.0213	0.6609	0.7304
GERMANY	all	8668	1471	0.8521	0.0034	0.8465	0.8576
	small	3111	823	0.8335	0.0054	0.8246	0.8423
	medium	2021	562	0.8683	0.0060	0.8584	0.8782
	large	3536	630	0.8552	0.0046	0.8476	0.8628
ITALY	all	1818	561	0.8051	0.0078	0.7921	0.8178
	small	745	287	0.8381	0.0105	0.8206	0.8553
	medium	355	158	0.8584	0.0127	0.8373	0.8790
	large	718	215	0.7777	0.0147	0.7536	0.8019
NETHERLANDS	all	134	36	0.8263	0.1086	0.6148	0.9585
	large	118	33	0.7935	0.1303	0.5654	0.9592
POLAND		93	28	0.9135	0.0417	0.8334	0.9664
ROMANIA		104	23	0.855	0.0672	0.7401	0.9553
SERBIA		80	25	0.6028	0.0776	0.4986	0.7335
SLOVENIA		84	17	0.9193	0.0383	0.8463	0.9687
SWEDEN	all	344	61	0.8696	0.0401	0.8085	0.9403
	small	235	48	0.8951	0.0400	0.8287	0.9588
SWITZERLAND	all	1188	221	0.5986	0.0174	0.5707	0.6281
	small	749	170	0.6105	0.0185	0.5806	0.6414
	medium	201	69	0.6886	0.0263	0.6441	0.7310
	large	238	44	0.6798	0.0285	0.6343	0.7276
TURKEY		84	18	0.8324	0.0627	0.7369	0.944
UNITED KINGDOM	all	350	85	0.8519	0.0829	0.6983	0.9612
	small	87	25	0.8606	0.0855	0.6887	0.9588
	large	226	60	0.8574	0.0785	0.7148	0.9611

Notes:* Highest Density Region, † Posterior mean of the efficiency score (r) for country j is reported. Posterior moments are computed based on 50,000 points generated from the Gibbs sampling algorithm. The end points of the 90% confidence region are the 5^{th} and the 95^{th} percentiles of the marginal densities. If total assets ≥1,000 millions dollars, the bank is large. Banks with total assets between 100 and 500 millions are small. Banks with total assets between 500 and 1,000 millions are of medium size.

Table 5.18: σ^2 - Posterior Means and Standard Deviation, 90% H.D.R.*

Countries\Bank size		Obs.	No. banks	σ^2	Post. S.D.	Q_5	Q_{95}
Pooled frontier	all	13970	2819	0.1347	0.0025	0.1307	0.1387
	small	5305	1479	0.1176	0.0045	0.1104	0.1250
	medium	2881	927	0.0809	0.0039	0.0746	0.0873
	large	5784	1269	0.1300	0.0035	0.1243	0.1358
CROATIA		121	26	0.0832	0.0157	0.0580	0.1100
DENMARK	all	375	78	0.0939	0.0125	0.0743	0.1153
	small	174	51	0.0989	0.0137	0.0771	0.1220
	large	132	39	0.0528	0.0144	0.0318	0.0784
FRANCE	all	527	171	0.0586	0.01121	0.0420	0.0785
	large	452	150	0.0475	0.00901	0.0341	0.0633
GERMANY	all	8668	1471	0.0329	0.0009	0.0314	0.0344
	small	3111	823	0.0222	0.0012	0.0202	0.0243
	medium	2021	562	0.0199	0.0012	0.0180	0.0221
	large	3536	630	0.0337	0.0012	0.0317	0.0357
ITALY	all	1818	561	0.0386	0.0024	0.0348	0.0427
	small	745	287	0.0226	0.0024	0.0188	0.0267
	medium	355	158	0.0181	0.0025	0.0143	0.0226
	large	718	215	0.0518	0.0056	0.0433	0.0615
NETHERLANDS	all	134	36	0.3548	0.0808	0.1998	0.4743
	large	118	33	0.3521	0.1022	0.1668	0.5038
POLAND		93	28	0.1796	0.0303	0.1356	0.2338
ROMANIA		104	23	0.1144	0.0301	0.0658	0.1644
SERBIA		80	25	0.0988	0.0660	0.0336	0.2332
SLOVENIA		84	17	0.0808	0.0156	0.0578	0.1083
SWEDEN	all	344	61	0.0602	0.0116	0.0418	0.0795
	small	235	48	0.0577	0.0106	0.0398	0.0746
SWITZERLAND	all	1188	221	0.0459	0.0095	0.0323	0.0630
	small	749	170	0.0428	0.0090	0.0296	0.0590
	medium	201	69	0.0323	0.0086	0.0203	0.0481
	large	238	44	0.0350	0.0117	0.0202	0.0571
TURKEY		84	18	0.0564	0.0233	0.0240	0.0986
UNITED KINGDOM	all	350	85	0.4026	0.0500	0.3111	0.4774
	small	87	25	0.6093	0.1113	0.4442	0.8063
	large	226	60	0.3134	0.0471	0.2306	0.3866

Notes:* Highest Density Region
Posterior moments are computed based on 50,000 points generated from the Gibbs sampling algorithm. The end points of the 90% confidence region are the 5^{th} and the 95^{th} percentiles of the marginal densities. If total assets $\geq$1,000 millions dollars, the bank is large. Banks with total assets between 100 and 500 millions are small. Banks with total assets between 500 and 1,000 millions are of medium size.

Slovenia is one of the most developed countries from the Central and South Eastern Europe that joined the European Union in 2004, and adopted the Euro in 2007, with a 2009 GDP per capita at 88 percent of the European Union average[17], so the results are not surprising even though according to the International Monetary Fund (IMF) 2007 country report, the banking industry suffers from over staffing especially in the state owned banks. The wages, still low comparative to the European Union average, keep the costs low in spite of a higher labor share. Nevertheless, our results show a higher mean efficiency compared to the 2007 IMF estimate of 82.6 percent (computed with commercial banking data covering years 1995 to 2005). As reported by Slovenia's Central bank, the country's banking system is comprised of 20 major commercial banks (out of which 17 banks are included in our analysis as in some years they registered total assets of more than 100 million dollars).

High mean efficiency scores are exhibited also by the following countries: Poland (above 90 percent), Denmark, Germany, Italy, Netherlands, Sweden, Romania, Turkey, UK and Croatia (between 81 and 90 percent).

In Poland, the banking industry is dominated by domestic players that according to the ECFIN [18] country focus report from May 2010 "were not involved in the purchase of toxic international assets", limiting themselves to providing standard banking services and expanding the infrastructure, reason for which their banking system sailed relatively well the financial crisis. The recession eventually lead reduction of the sector's profits (that dropped by 45 percent in 2009). On the other hand, the market has a big potential for growth[19], the fees and commission revenues are relatively high due to the low competitive pressure. Nevertheless, the 2008 and 2009 effort to increase the number of agencies and branches is expected to lead to higher future operational expense of the sector.

[17]in purchasing power standards, according to the Eurostat Tables

[18]Economic analysis from the European Commissions Directorate-General for Economic and Financial Affairs

[19]since according to the same source 1.3 million accounts were opened in 2009 alone and more were expected to be opened in the future.

At the end of the spectrum, Serbia, a country that following World World I formed with other Slavic nations the former Republic of Yugoslavia, reclaimed its independence in 2006 and in spite of several years of spectacular economic growth (from 6.3 percent in 2005, to 8.7 percent in 2008), it's been plagued with a lot of the problems faced by transition economies: corruption, high inflation rates, slow structural change of the economy (privatization of large firms, including banks gained momentum only after 2004) and it remained very vulnerable to external shocks. Under these circumstances, the low efficiency score is not surprising.

Low overall efficiency scores are also registered by France (66.55 percent), suggesting that relatively to their own national frontier, there is a lot of room for improving cost efficiency.

The Dutch ($\bar{\sigma}^2 = 0.3548$), the English ($\bar{\sigma}^2 = 0.4026$) banks seem to be the least homogeneous relatively to their own frontier, while the German ($\bar{\sigma}^2 = 0.0329$), the Italian ($\bar{\sigma}^2 = 0.0386$), the Turkish ($\bar{\sigma}^2 = 0.0564$) and the Swiss ($\bar{\sigma}^2 = 0.0459$) are the most homogeneous.

Previous investigations of the relationship between bank size and efficiency found slighter higher cost efficiencies for the largest banks, while in terms of profit efficiency, the small banks exhibited a higher level (Berger and Mester 1997)[20].

For the countries that have enough observations to allow the analysis of cost frontiers according to bank size, we do not find high differences in terms of cost efficiency between the defined classes of banks. The medium and large size banks seem to be slightly more efficient relative to their own frontier in Switzerland (mean efficiency score of 68.86 percent and respectively 67.98 percent compared to the small banks that have a mean efficiency score of 61.05 percent). In Italy the medium and small banks are slightly more efficient (mean efficiency score of 83.81 percent and respectively 86.83 percent compared to the large banks' mean efficiency score of 77.77 percent), while in Denmark, the small size banks are more

[20] using Translog an Fourier functional forms and data from 6,000 U.S. commercial banks that were in continuous existence with complete information over the six-year period 1990-95.

efficient relative to their own frontier (mean efficiency score of 91.53 percent), compared to the large size banks that have a lower mean efficiency score (86.28 percent).

Germany and United Kingdom do not exhibit significant differences between the three categories of bank size considered. In Germany, regardless of the size, the efficiency scores are very similar (ranging from 83.35 percent for the small banks to 86.83 percent for the medium banks), while in United Kingdom, the small banks have a mean efficiency score of 86.06 percent while the large banks have a mean efficiency score of 85.74 percent.

In Italy, the large banks ($\bar{\lambda} = 0.2516$) seem to bring down the results for the country's efficiency, the small ($\bar{\lambda} = 0.1767$) and medium banks ($\bar{\lambda} = 0.1528$) exhibiting higher cost efficiency.

5.4 Posterior Marginal Densities for λ, Efficiency Score and σ^2

For completeness, this section contains marginal density plots for λ, σ^2 and efficiency score for each country (Figure 5.28 through Figure 5.41). Intuitively, there is no reason to anticipate a priori that these density plots will be normally distributed. For example, conditional densities for the λ's are gamma and the posterior marginal density is based on integrating over multiple parameters.

In general, the posterior marginal densities for λ tend to appear more asymmetric for countries that are most efficient due to truncation of the inefficiency distribution or for those with fewer observations. Also, given the properties of the gamma distribution and looking at the formulas of the full conditional densities, it can be noted that the number of observations from each country, the heterogeneity of the data will influence the shape of the posterior marginal densities in terms of symmetry, smoothness, width.

In the case of the countries for which the data allowed a sample split according to bank size (Denmark - Figure 5.29, Germany - Figure 5.31, Italy - Figure 5.32, Switzerland - Figure 5.39 and UK - Figure 5.29), we drew plots for each of the considered scenarios (national frontier, small banks, medium banks, and/ or large banks).

An interesting case that summarizes what we observe with these posterior marginal densities is Denmark (Figure 5.29). If we look at the plots for λ and the efficiency score, we observe relatively symmetric, almost normal distributions. As we split the data and draw the plots for the large and small banks, we can see that the posterior marginal distributions for the two parameters look asymmetric. This behavior can be explained on the one hand by the lower number of observations in the split datasets according to bank size versus the national frontier and on the other hand by the higher efficiency scores of the large and small banks compared to the national frontier case that includes all banks. The asymmetric shapes can be found in the λ and the efficiency score posterior marginal density plots for other countries with low number of observations (Croatia - Figure 5.28, Netherlands - Figure 5.33, Poland - Figure 5.34 or Slovenia - Figure 5.37). For countries like Romania (Figure 5.35), UK (Figure 5.41) or (Figure 5.40), the posterior marginal distributions of λ and the efficiency score show lack of smoothness due to the small number of observations and possible clustering of banks in certain areas of the frontiers.

The same symmetric, almost normal aspect we can also observe in the case of the posterior marginal distributions for σ^2, especially for the countries with a higher number of observations.

Croatia

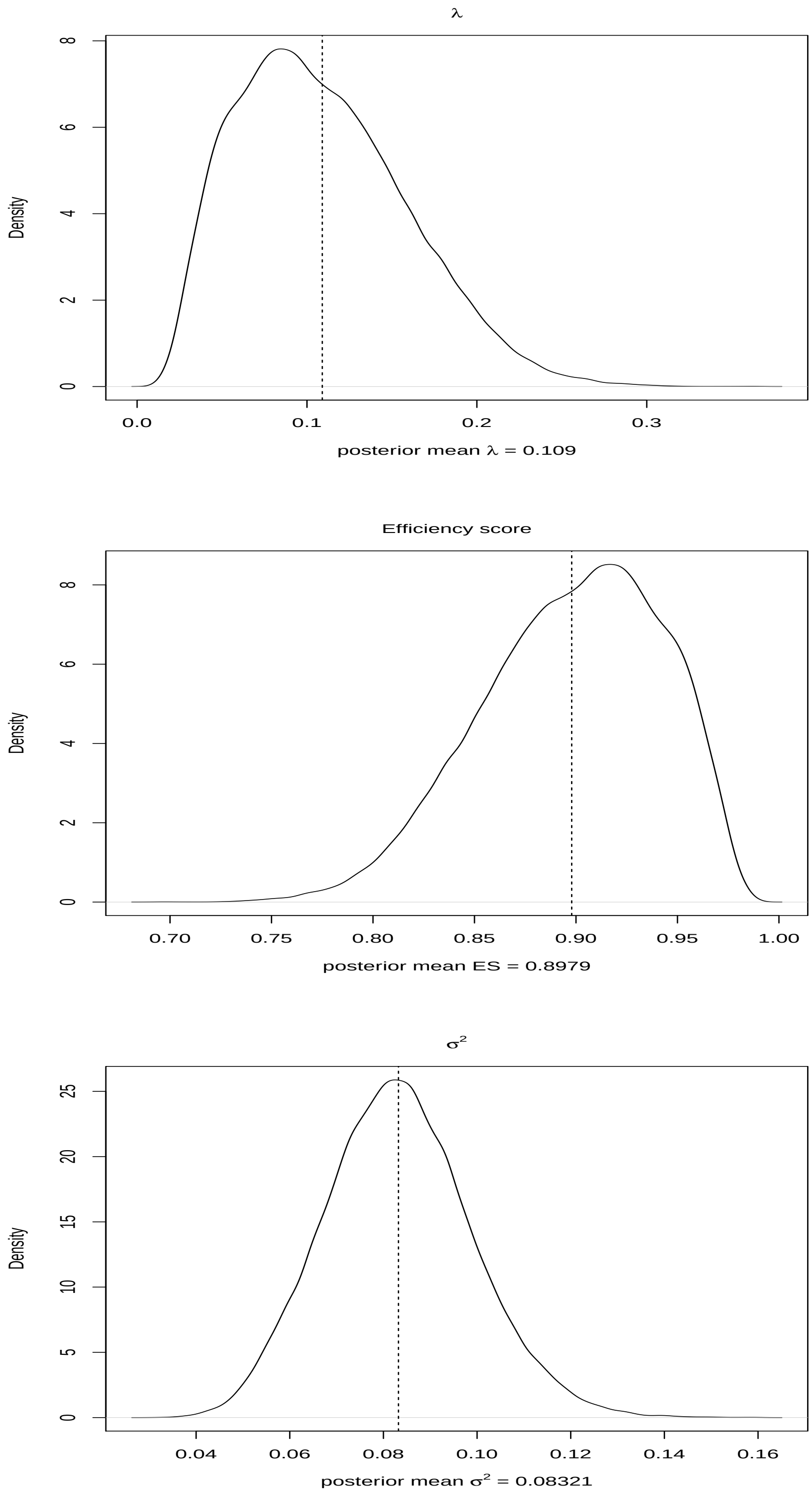


Figure 5.28: Posterior Marginal Densities for λ, Efficiency Score and σ^2.

Denmark

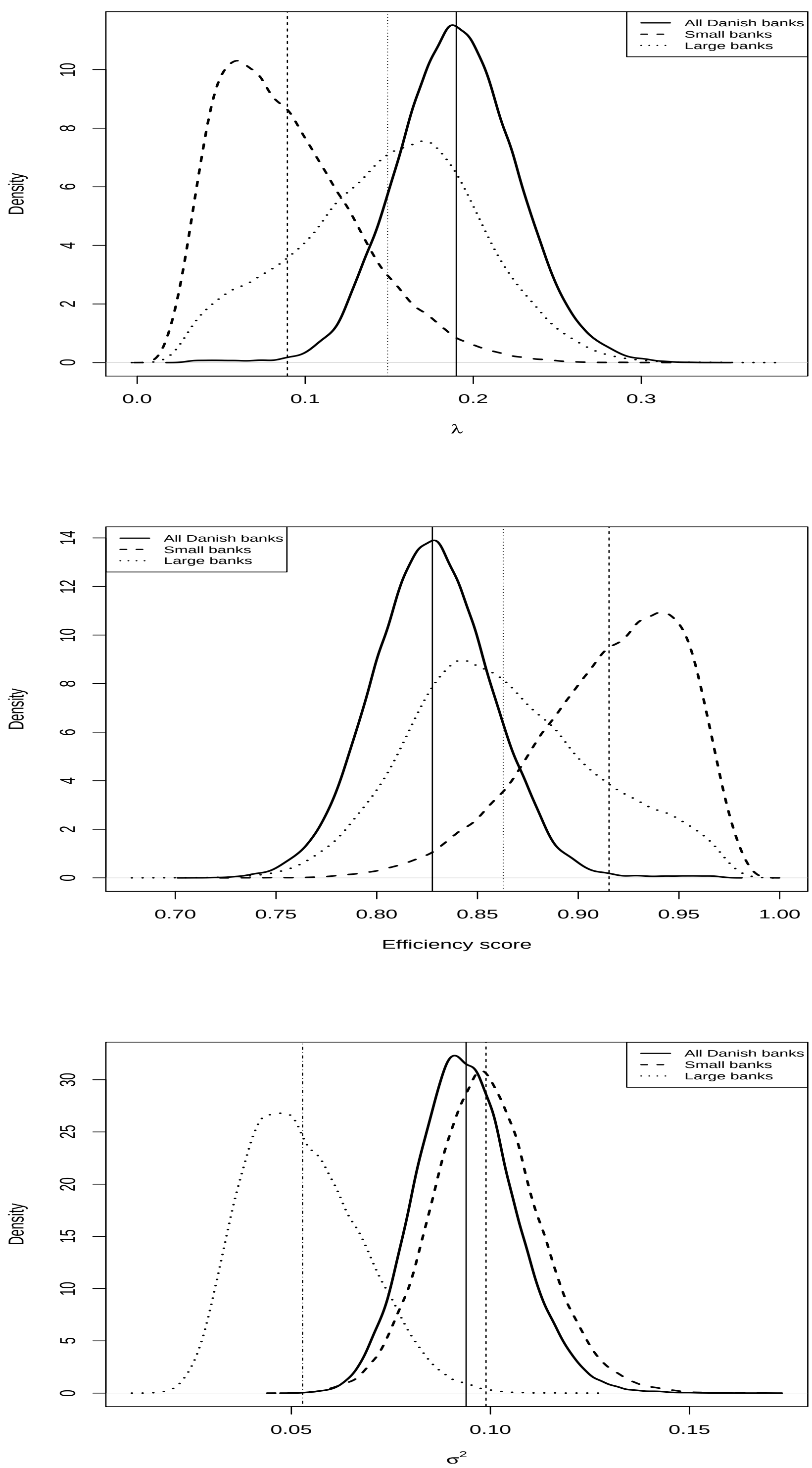


Figure 5.29: Posterior Marginal Densities for λ, Efficiency Score and σ^2.

France

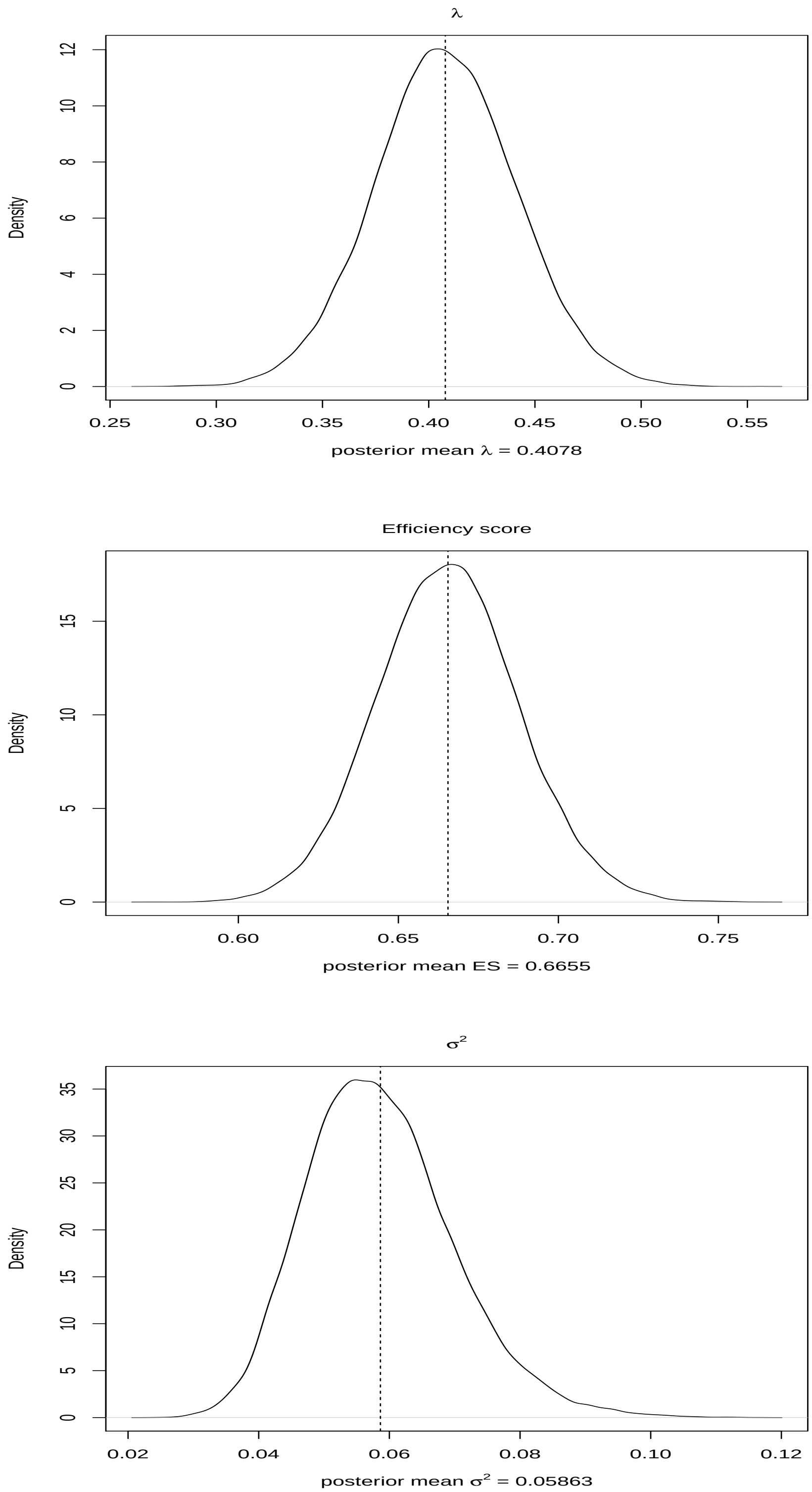


Figure 5.30: Posterior Marginal Densities for λ, Efficiency Score and σ^2.

Germany

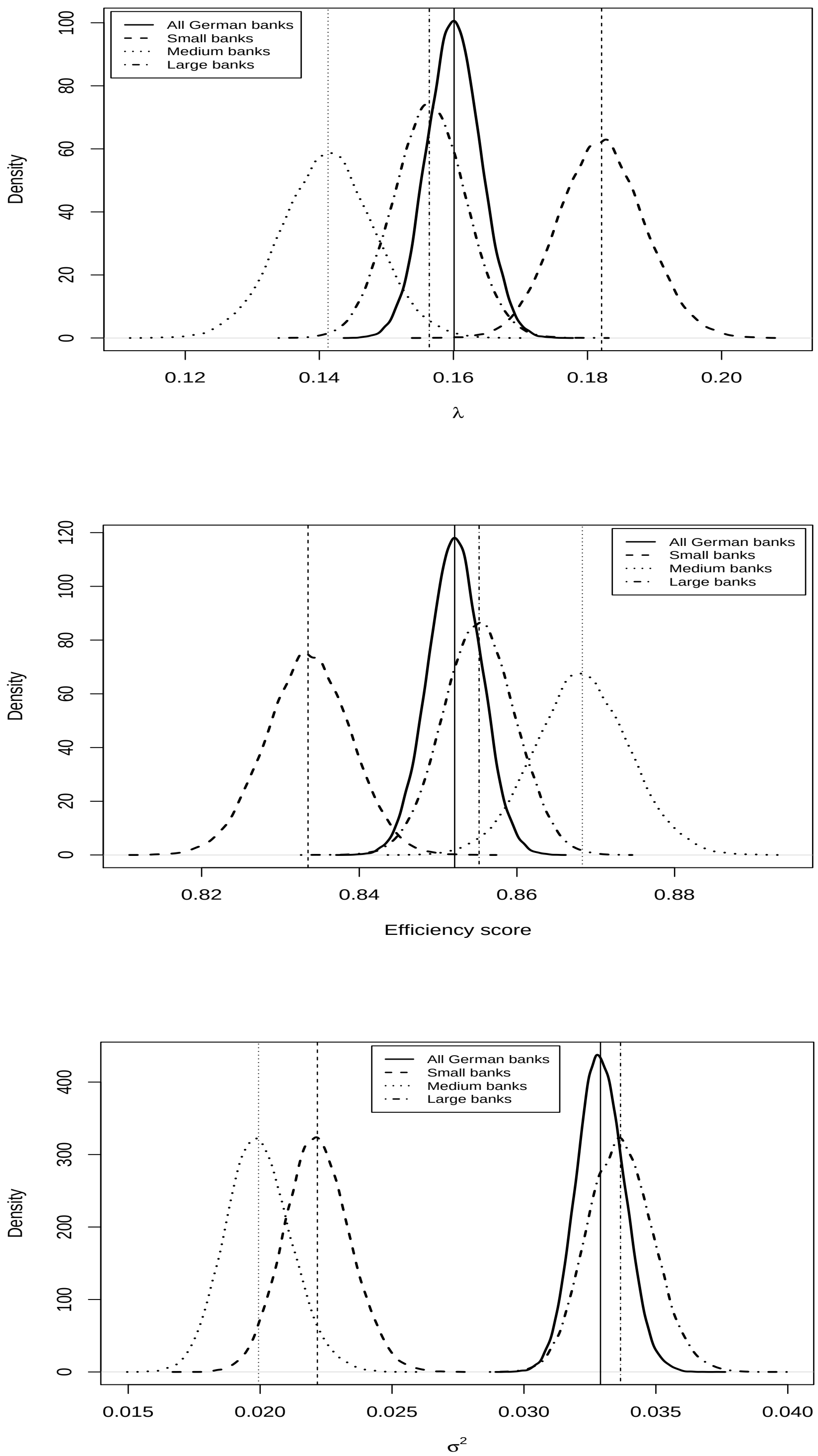


Figure 5.31: Posterior Marginal Densities for λ, Efficiency Score and σ^2.

Italy

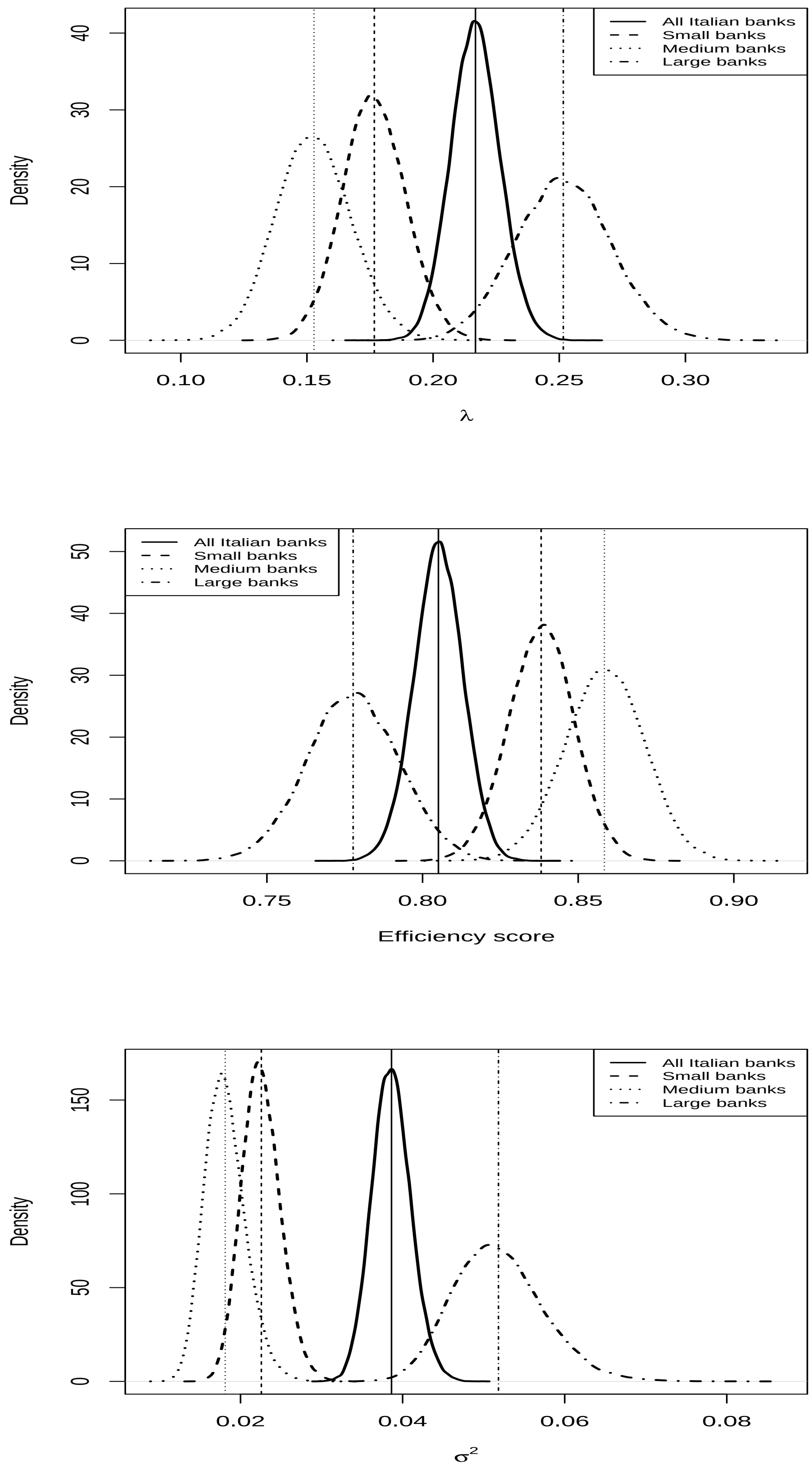


Figure 5.32: Posterior Marginal Densities for λ, Efficiency Score and σ^2.

Netherlands

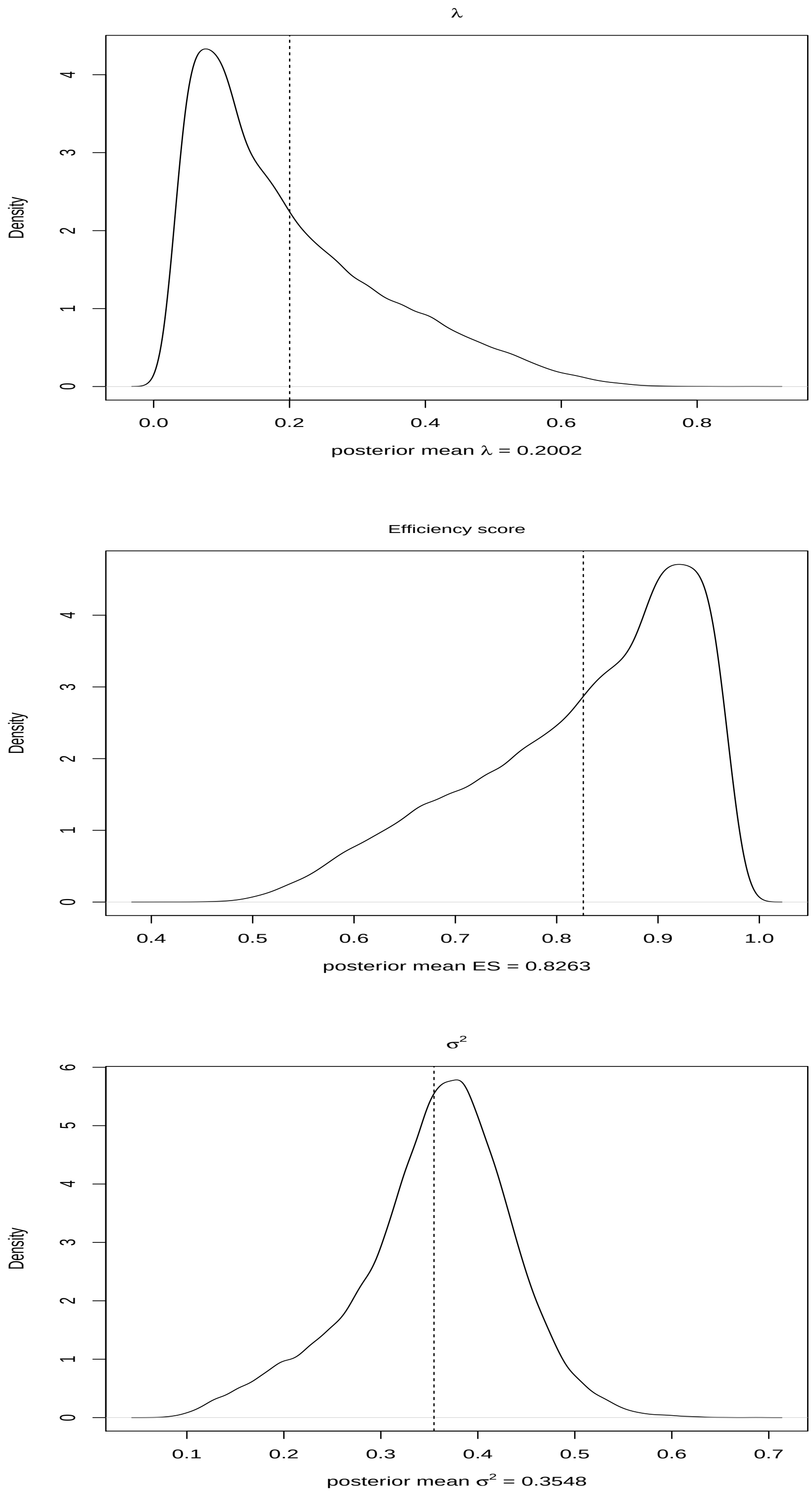


Figure 5.33: Posterior Marginal Densities for λ, Efficiency Score and σ^2.

Poland

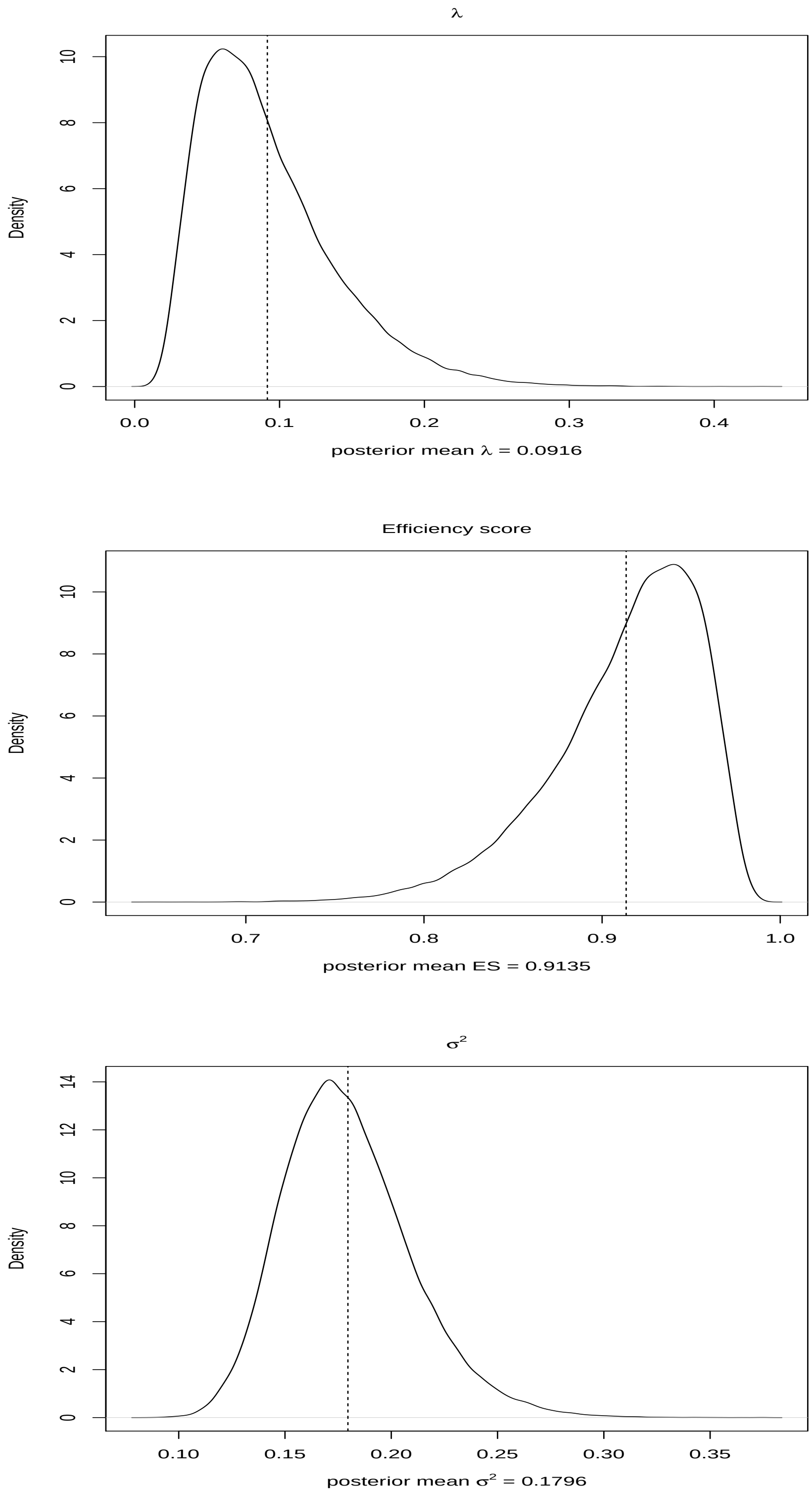


Figure 5.34: Posterior Marginal Densities for λ, Efficiency Score and σ^2.

Romania

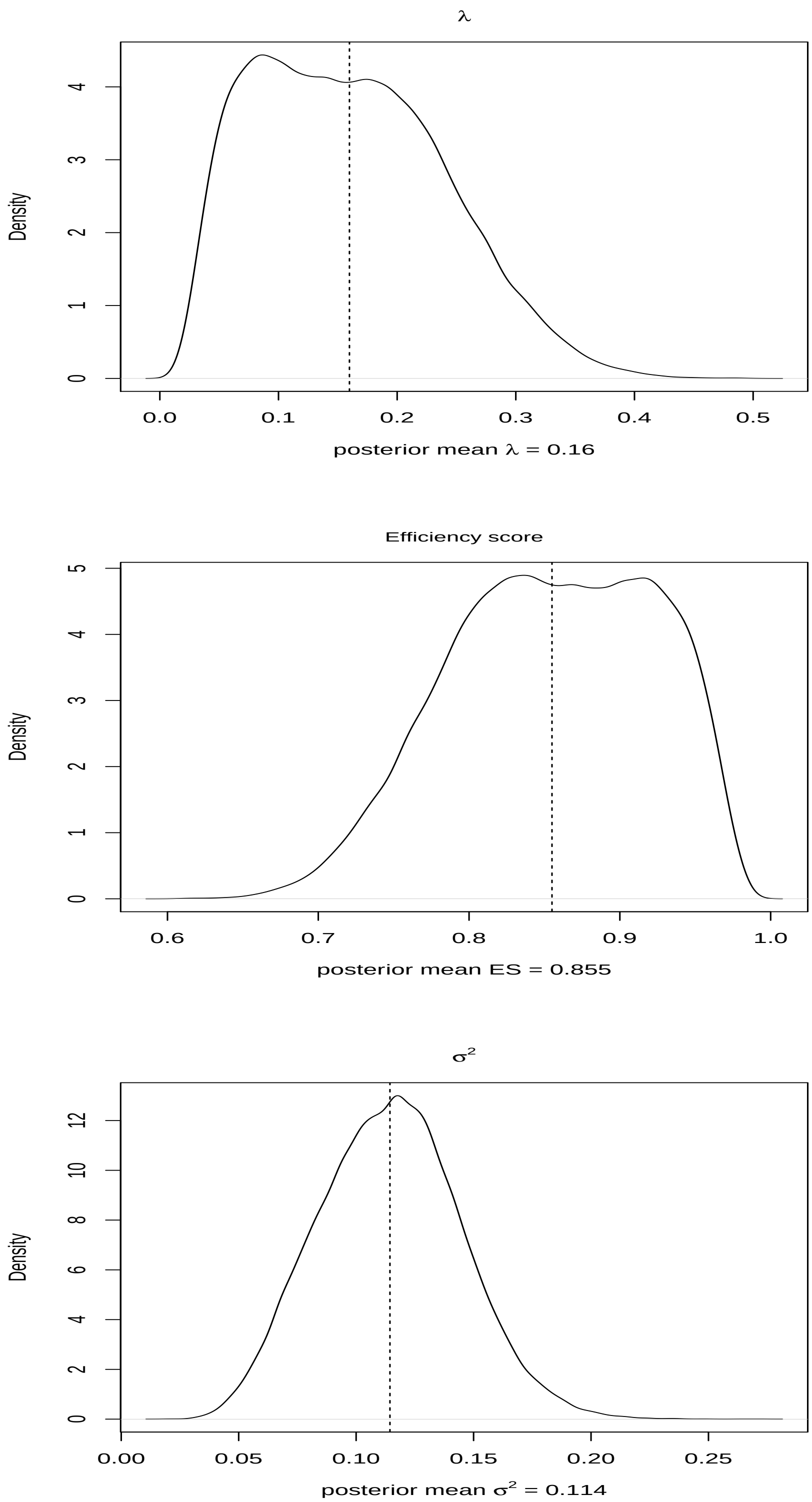
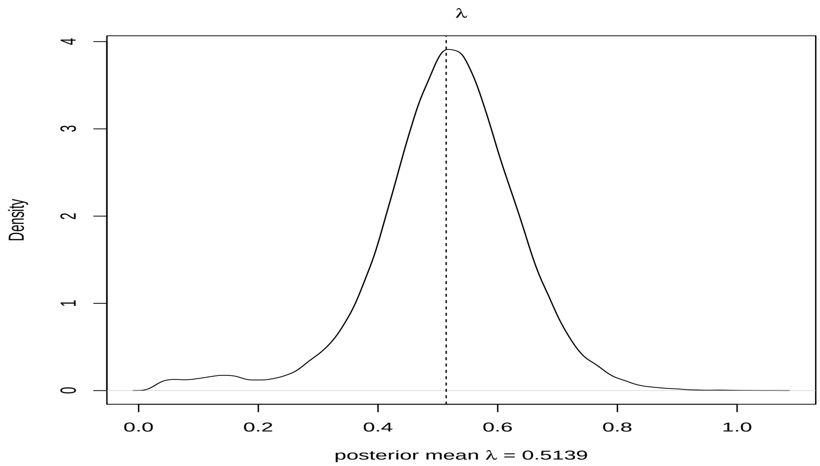
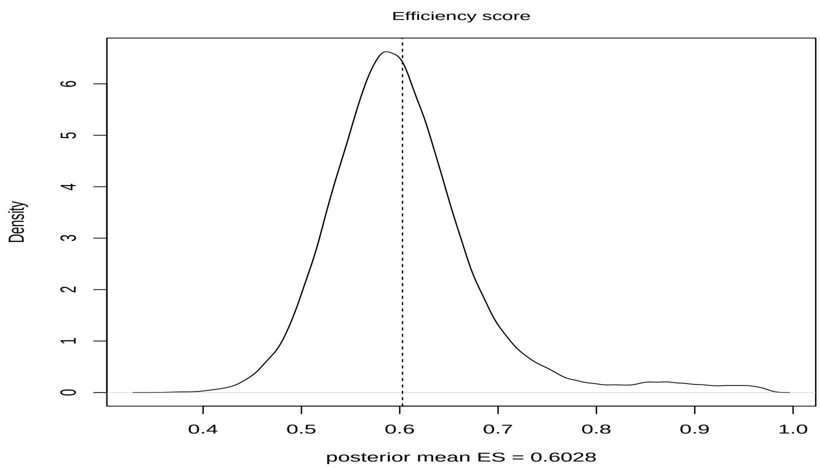


Figure 5.35: Posterior Marginal Densities for λ, Efficiency Score and σ^2.

Serbia





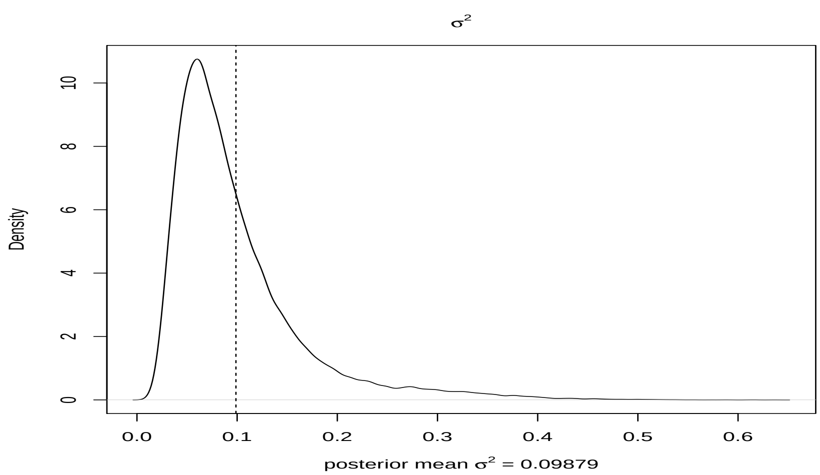


Figure 5.36: Posterior Marginal Densities for λ, Efficiency Score and σ^2.

Slovenia

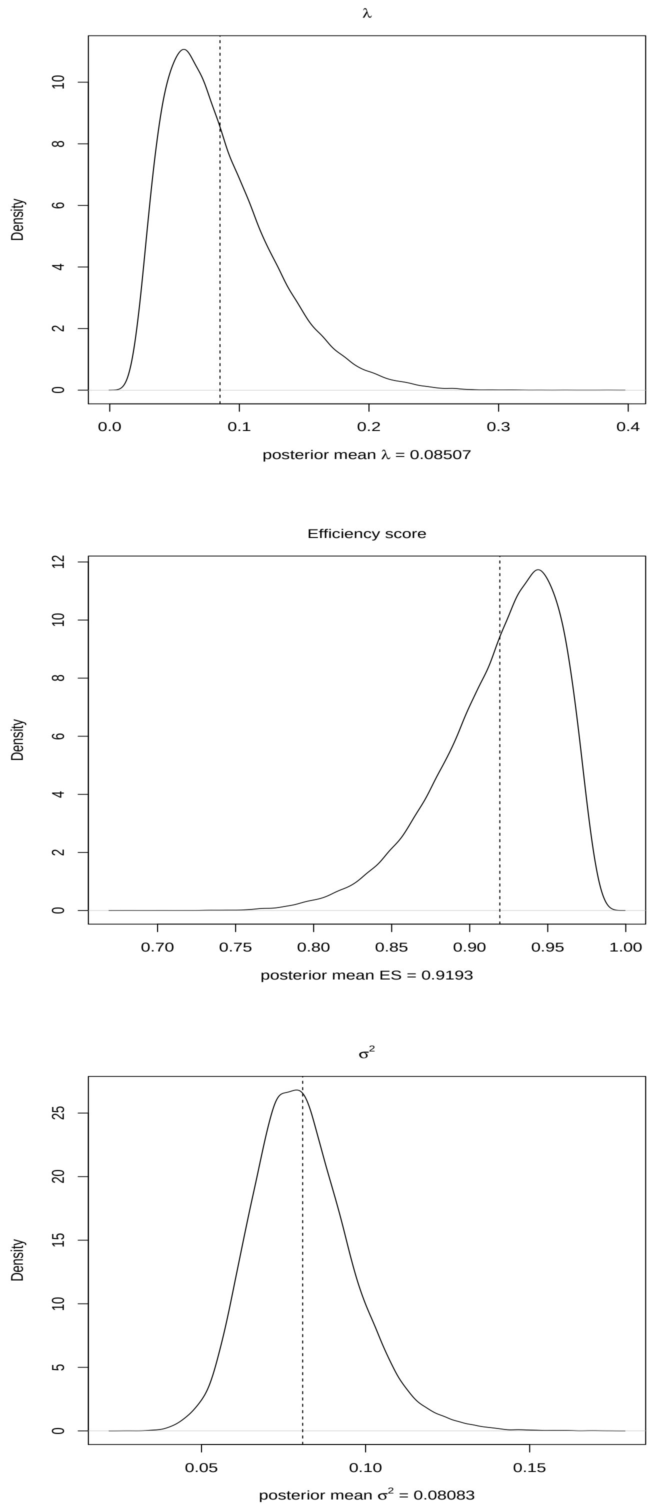


Figure 5.37: Posterior Marginal Densities for λ, Efficiency Score and σ^2.

Sweden

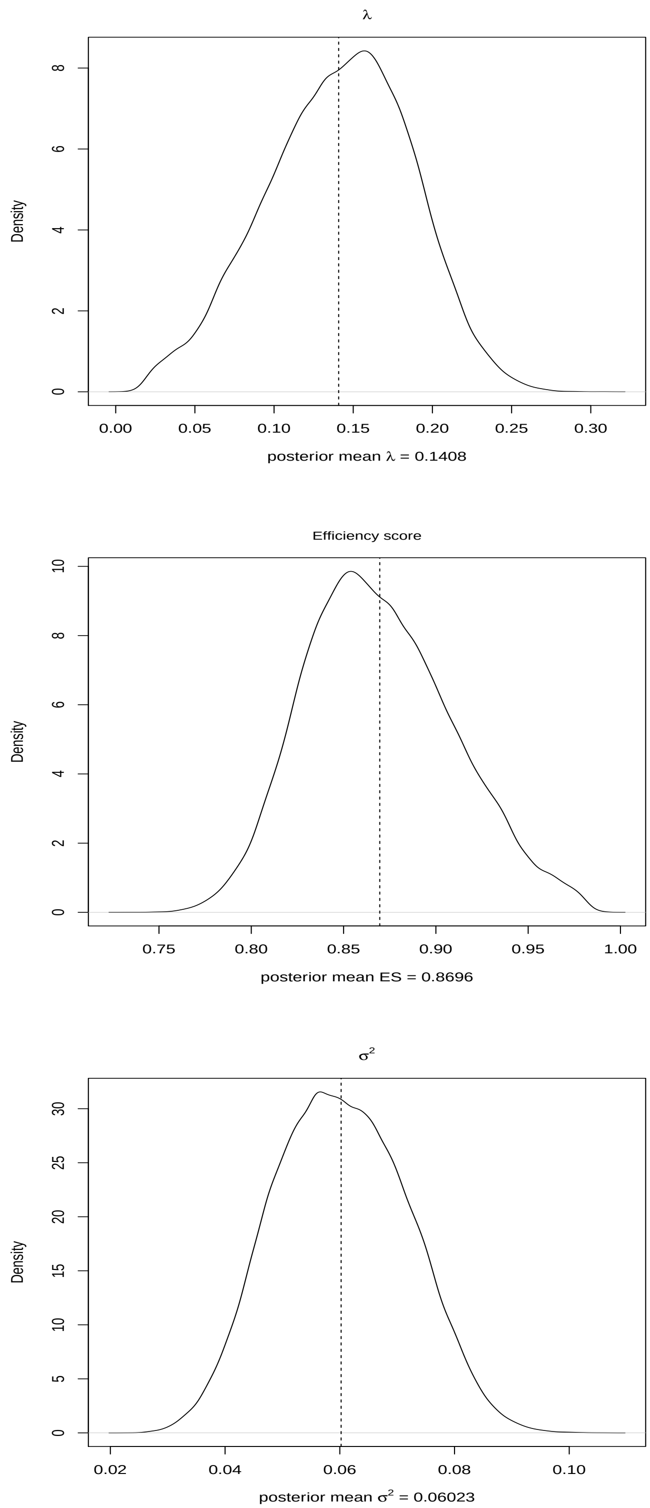


Figure 5.38: Posterior Marginal Densities for λ, Efficiency Score and σ^2.

Switzerland

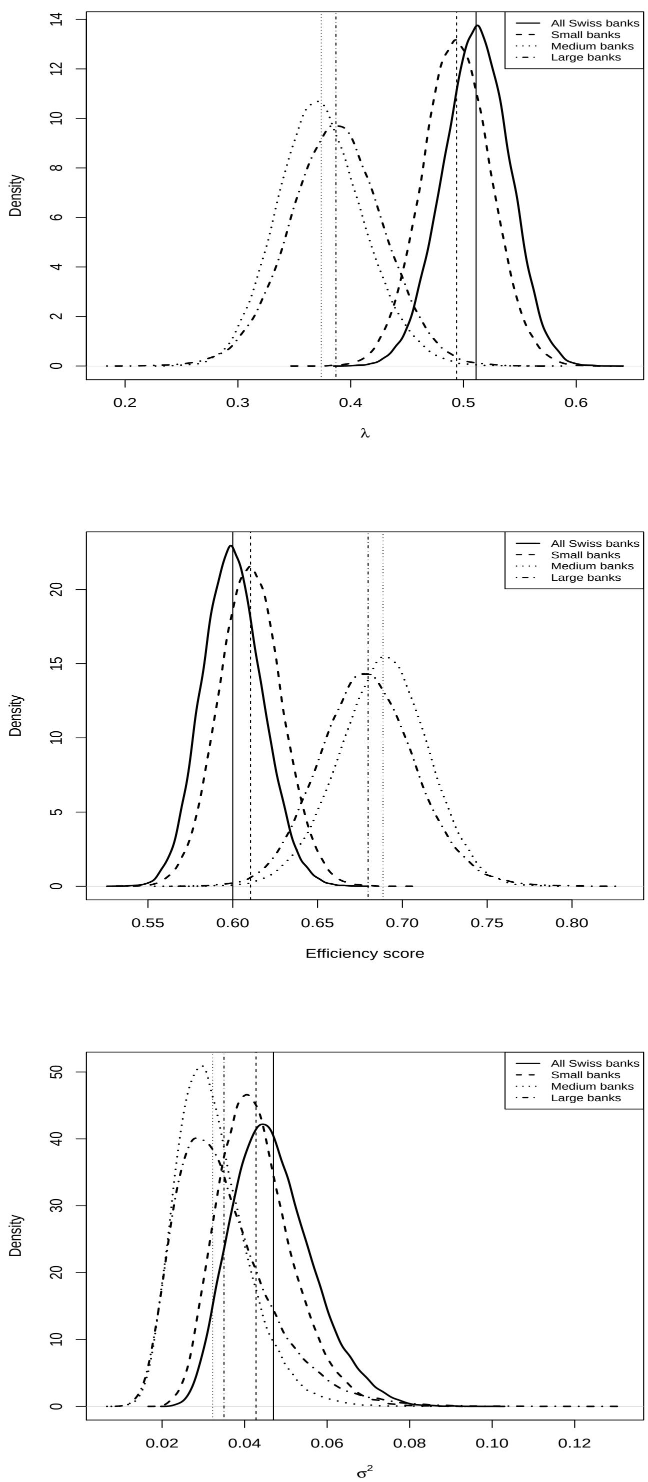


Figure 5.39: Posterior Marginal Densities for λ, Efficiency Score and σ^2.

Turkey

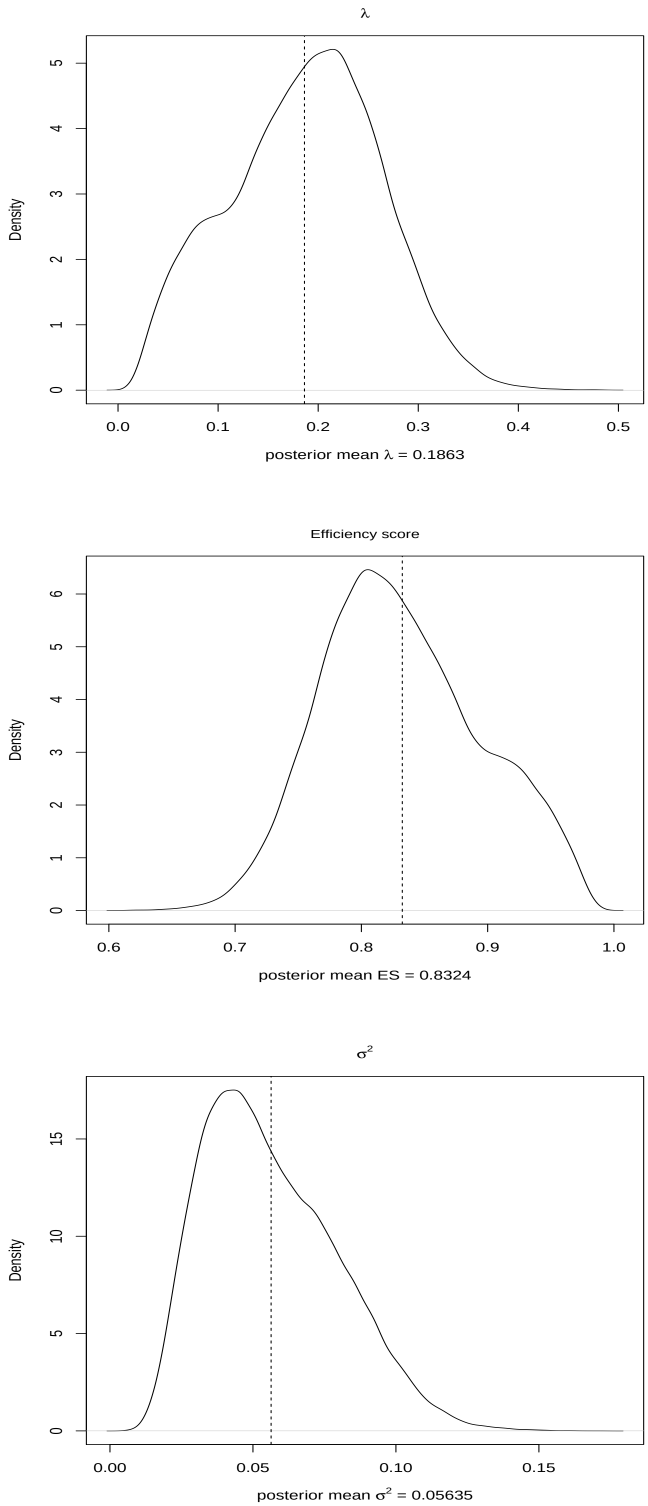


Figure 5.40: Posterior Marginal Densities for λ, Efficiency Score and σ^2.

United Kingdom

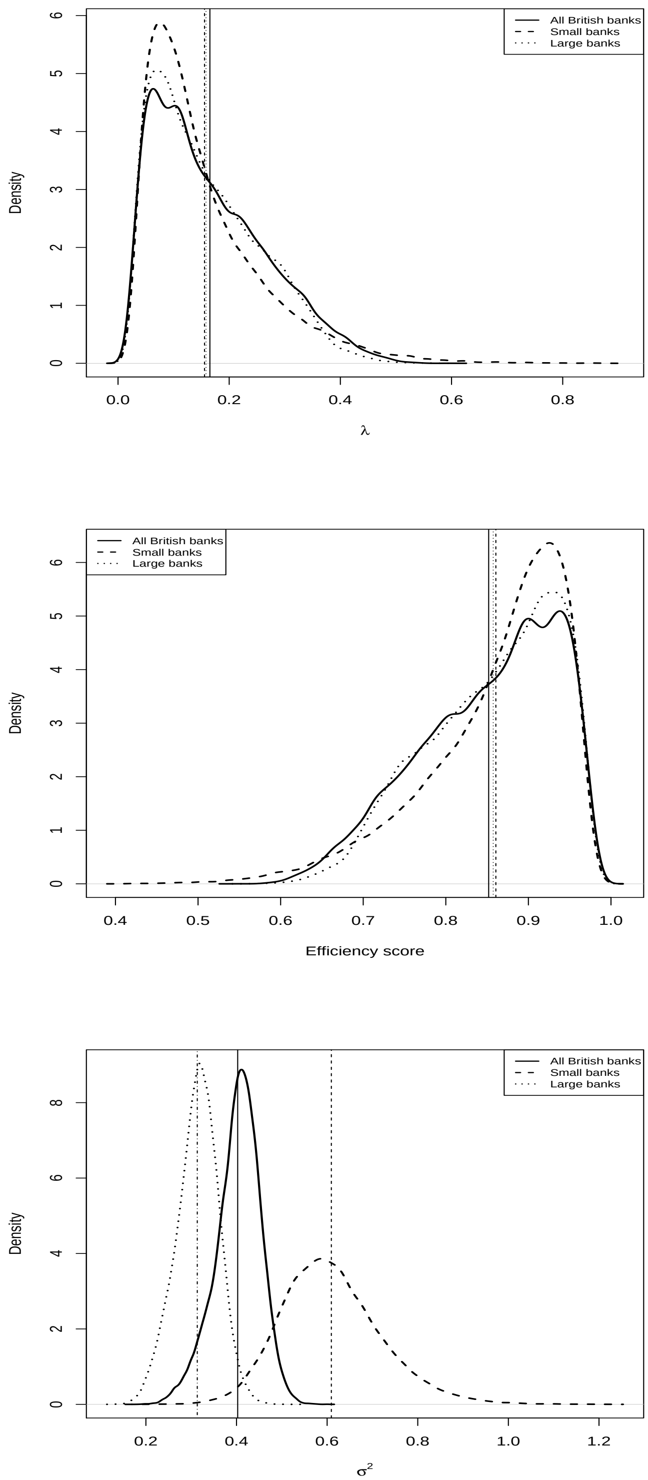


Figure 5.41: Posterior Marginal Densities for λ, Efficiency Score and σ^2.

5.5 Conclusions

This chapter focuses on an analysis of the efficiency of European banks based on individual cost frontiers for 14 countries. When possible, we also investigate the possibility that bank size may have an impact on the efficiency level.

Results for the technology parameters indicate substantial differences across countries and bank size. Plots of the technology frontier for cost versus a single input price or output holding other factors constant generally confirm the idea that the technologies appear to differ across countries.

The presence of multiple frontiers is further pointed out by the difference in results obtained for economies of scales computed for selected banks against the domestic frontier versus the pooled frontier. We observe that in reference to a pooled frontier, the posterior means of the economies of scale tend to consistently be higher than one even in the case of the large banks, while with respect to the national frontier, we sometimes get smaller returns to scale or highest density regions that include one. This suggests that the banks could reduce costs by increasing output, which can translate into an increased number of mergers/takeovers in the future especially if they decide to exploit the advantages of the single market for financial services.

Nevertheless, in the wake of the recent economic and financial crisis, these advantages in terms of reducing costs by increasing bank size might be offset by the risks of systemic failures that this process could bring about as some banks might become "too big to fail".

In terms of efficiency, we find that the most efficient banks relative to their own frontier are the ones from Slovenia (mean efficiency score of 91.93 percent). Results suggest that the least efficient banks are the ones from Switzerland (mean efficiency score of 59.86 percent) and Serbia (mean efficiency score of 60.28 percent).

Given that the frontiers may allow for substantial variation in cost structure across countries, cross-country comparisons should be viewed with some caution. One nation could appear quite efficient because its banks are clustered tightly around a high-cost frontier while another could appear inefficient due to dispersion of costs around a lower cost frontier. Furthermore, earlier results suggest substantial variation in frontiers across countries. To address this issue, we explore measuring country specific efficiency versus common frontier in Chapter 6.

Chapter 6
Multiple Lambda Model: Comparing the Cost Efficiency of Banks Across Countries

6.1 Introduction

The last chapter contained estimates of efficiency based on allowing for different frontiers in each country. In this chapter, the data is pooled - banks in all countries share a common frontier. The basic approach is again a Bayesian stochastic frontier model, but modified in this case to allow for both λ and σ^2 to vary across country. Furthermore, we incorporate an informative prior on the model parameters in preparation for a later model in chapter 7 (though the variances are set large enough to essentially mimic the diffuse prior from chapter 5). For a select group of banks, we derive the economies of scale.

After presenting the model specification and methodology, the chapter goes over the empirical results and ends with conclusions. For completeness, section 6.4 includes posterior marginal densities for λ, efficiency score, and σ^2.

6.2 Model Specifications and Methodology

Chapter 5 presents the basis of the stochastic cost frontier model that is also employed in the current approach with some modifications. Because we are estimating a common frontier, we assume a shared technology for all the countries in the dataset (the translog parameters, β's, are the same for all countries, with $\boldsymbol{\beta}= (\beta_1, ..., \beta_{10})^T$ the 10×1 common technology vector).

Given that we work with the pooled dataset that stacks all the observations together, we denote the $N \times 10$ independent variables matrix by X, with $N = N_{HR} + ... + N_{UK} = \sum_{j=1}^{14} N_j$ total number of observations obtained by adding up the number of observations from each country (i.e. $N_{HR} = N_1$ being the number of bank-year observations for Croatia, etc.). The matrix X is obtained by stacking up the independent variables matrices from all the countries (i.e. $X_{HR} = X_1$ for Croatia, $X_{DK} = X_2$ for Denmark, etc.) and $\mathbf{y}$ is the $N \times 1$ stacked vector of total costs constructed similarly to X. Let $K_j = \sum_{n=1}^{j} K_n$ and $K_0 = 0$. The rows from 1 to K_1 are the N_1 stacked observations for Croatia (X_{HR}) and in general, the rows from $K_{j-1}+1$ to K_j are the N_j stacked observations for country j, for $j = 1, ..., 14$.

While we ignore the bank's country of provenience when it comes to technology, we will allow for differences between countries by including unequal variances in the model. The data variance-covariance matrix (Σ) is assumed to be a $N \times N$ diagonal matrix that is not proportional to the identity matrix. The variance corresponding to the n's observation is inserted on row n. The covariance terms are equal to zero. As a result, we have 14 diagonal matrices ($\Sigma_{HR} = \Sigma_{u_1}$, $\Sigma_{DK} = \Sigma_{u_2}$, etc.) of dimensions $N_j \times N_j$, where $j = 1, ..., 14$ that correspond to each country's variance-covariance matrix (i.e. $\Sigma_{HR} = \text{diag}[\sigma^2_{HR}]$, etc.). Note that $\Sigma_{HR} = \sigma^2_{HR} \times I$, where I is the identity matrix.

The inefficiency terms, $v_{ij} \sim EXP(\lambda_j)$ follow exponential distributions, and we construct $\mathbf{v} = (\mathbf{v}_{HR}, \mathbf{v}_{DK}, ..., \mathbf{v}_{UK})^T = (\mathbf{v}_1, \mathbf{v}_2, ..., \mathbf{v}_{14})^T$, the stacked inefficiency vector of dimension $N \times 1$ ($\mathbf{v}_{HR} = \mathbf{v}_1$, etc.). Similarly, $\boldsymbol{\lambda} = (\lambda_{HR}, \lambda_{DK}, ..., \lambda_{UK})^T$ is the stacked vector of inefficiency parameters with $\lambda_{HR} = \lambda_1$, $\lambda_{DK} = \lambda_2$, etc.

The statistical noises $u_{ij} \sim N(0, \sigma_{u_j}^2)$ are assumed to be normally distributed, where i is the bank-year index and $j = 1, ..., 14$ is the country index, with $\mathbf{u} = (\mathbf{u}_{HR}, \mathbf{u}_{DK}, ..., \mathbf{u}_{UK})^T = (\mathbf{u}_1, \mathbf{u}_2, ..., \mathbf{u}_{14})^T$ the stacked vector of dimension $N \times 1$.

$$X = \begin{pmatrix} X_{HR} \\ X_{DK} \\ X_{FR} \\ \vdots \\ X_{UK} \end{pmatrix}, \quad \mathbf{y} = \begin{pmatrix} \mathbf{y}_{HR} \\ \mathbf{y}_{DK} \\ \mathbf{y}_{FR} \\ \vdots \\ \mathbf{y}_{UK} \end{pmatrix}, \quad \Sigma = \begin{pmatrix} \Sigma_{HR} & 0 & \cdots & & & 0 \\ 0 & \Sigma_{DK} & 0 & \cdots & & 0 \\ 0 & 0 & \Sigma_{FR} & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & \cdots & 0 & 0 & \Sigma_{UK} \end{pmatrix}$$

Using the notations defined above, the model can be written in matrix form as:

$$\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \mathbf{v} + \mathbf{u}$$

.

We complete the model specification by choosing the priors[1] and in doing so, we rely on Koop, Osiewalski and Steel (1994), but also on Geweke (2005) and Gelman et al. (2004) as follows:

- an informative prior for $\boldsymbol{\beta} \sim N(\boldsymbol{\beta}_p, {H_p}^{-1})$, where $\boldsymbol{\beta}_p$ is a 10×1 vector of constants and H_p is a 10×10 positive definite matrix of constants. We specify $\boldsymbol{\beta}_p = (0, 0, ..., 0)^T$ as the null vector and construct the prior precision matrix as a diagonal matrix such that the prior variance on linear terms is equal to 10 and on the quadratic or interaction terms is equal to 1 ($\mathrm{H}_p{}^{-1}$ diagonal elements are $[10, 10, 1, 10, 1, 10, 1, 1, 1, 1]$) [2].

[1] when choosing informative priors for ${\lambda_j}^{-1}$ and $\sigma_{u_j}^{-2}$, the posterior is ensured to be proper (integrate to one).

[2] because it is expected that the posterior means of the parameters from the quadratic and interaction terms are smaller than the ones for the linear terms. The variance terms need to be chosen taking that into account. Virtually all previous studies including the results in chapter 5 confirm this expectation.

We introduce an informative prior for $\boldsymbol{\beta}$ as a reference and build up towards the next chapter's model that requires the use of an informative prior. Nevertheless, due to our choice of constants for both $\boldsymbol{\beta}_p$ and H_p, the results are similar to choosing a flat prior. In other words, even though informative, the prior used is weak.

- a gamma[3] prior[4] for each $\sigma_{u_j}^{-2}$, with $j = 1, ..., 14$: $\pi(\sigma_{u_j}^{-2}) = f_G(\sigma_{u_j}^{-2}|\frac{\tau_j}{2}, \frac{s_{p_j}^2}{2})$. By setting for all j's $\tau_j = 1$ and $s_{p_j}^2 = 0.10$, we are choosing a weak prior on each $\sigma_{u_j}^2$.
- a gamma prior for each $\lambda_j{}^{-1}$, with $j = 1, ..., 14$: $\pi(\lambda_j{}^{-1}) = f_G(\lambda_j{}^{-1}|1, -\ln(r^*))$, where r^* is the prior mean for efficiency. We set r^* equal to 0.875[5].

The full conditional distributions are derived based on the same references as used when choosing the priors:

- $\boldsymbol{\beta}|\text{data}, \mathbf{v}, \Sigma, \boldsymbol{\lambda} \sim N(\bar{\boldsymbol{\beta}}, \bar{\mathrm{H}}^{-1})$, where $\bar{\mathrm{H}} = \mathrm{H}_p + \mathrm{X}^T\Sigma^{-1}\mathrm{X}$ and $\bar{\boldsymbol{\beta}} = \bar{\mathrm{H}}^{-1}(\mathrm{H}_p\boldsymbol{\beta}_p + \mathrm{X}^T\Sigma^{-1}\mathrm{y}^*)$, with $\mathrm{y}^* = \mathbf{y} - \mathbf{v}$. If we denote $\widehat{\mathrm{H}} = \mathrm{X}^T\Sigma^{-1}\mathrm{X}$ and $\widehat{\boldsymbol{\beta}} = (\mathrm{X}^T\Sigma^{-1}\mathrm{X})^{-1}\mathrm{X}^T\Sigma^{-1}\mathbf{y}^*$, then it can be observed that $\bar{\mathrm{H}} = \mathrm{H}_p + \widehat{\mathrm{H}}$ and $\bar{\boldsymbol{\beta}} = \bar{\mathrm{H}}^{-1}[\mathrm{H}_p\boldsymbol{\beta}_p + \widehat{\mathrm{H}}\widehat{\boldsymbol{\beta}}]$. At a closer look, it turns out that $\widehat{\boldsymbol{\beta}}$ and $\widehat{\mathrm{H}}^{-1}$ are actually the GLS estimators for the model parameters and variance, which intuitively makes sense for a model with unequal variance.
- $\sigma_{u_j}^{-2}|\text{data}, \sigma_{u_1}^{-2}, ..., \sigma_{u_{j-1}}^{-2}, \sigma_{u_{j+1}}^{-2}, ..., \sigma_{u_{14}}^{-2}, \mathbf{v}, \boldsymbol{\beta}, \lambda$ is gamma distributed, for each country j: $f_G(\sigma_{u_j}^{-2}|\frac{N_j+\tau-2}{2}, \frac{SSE_j+s_p^2}{2})$, where $SSE_j = (\mathrm{y}_\mathbf{j}{}^* - \mathrm{X}_j\bar{\boldsymbol{\beta}})^T(\mathrm{y}_\mathbf{j}{}^* - \mathrm{X}_j\bar{\boldsymbol{\beta}})$. In other words, $\sigma_{u_j}^2$ for country j will be sampled based on the observations for country j (rows $K_{j-1}+1$ to K_j of the X matrix).
- $\lambda_j{}^{-1}|\text{data}, \lambda_1{}^{-1}, ..., \lambda_{j-1}{}^{-1}, \lambda_{j+1}{}^{-1}, ..., \lambda_{14}{}^{-1}, \mathbf{v}, \boldsymbol{\beta}, \Sigma$ is gamma distributed: $f_G(\lambda^{-1}|N_j + 1, \mathbf{v_j}^T\mathbf{i_{N_j}} - \ln(r^*))$, where $\mathbf{i_{N_j}}$ is a $N_j \times 1$ vector of ones. As before, λ_j for country j will be sampled based on the observations for country j (elements $K_{j-1}+1$ to K_j of the inefficiency vector, $\mathbf{v}$).

[3] where $f_G(.|\nu_1, \nu_2)$ is a gamma density with mean ν_1/ν_2 and variance ν_1/ν_2^2
[4] following Fernandez, Osiewalski, and Steel (1997)
[5] following Koop, Osiewalski and Steel (1994) and van den Broek, Koop, Osiewalski and Steel (1994).

- $\mathbf{v_j}|\text{data}, \mathbf{v_1}, ..., \mathbf{v_{j-1}}, \mathbf{v_{j+1}}, ..., \mathbf{v_{14}}, \boldsymbol{\beta}, \Sigma, \lambda$ is drawn from a truncated normal distribution[6]: the inefficiency of each bank, $v_{ij} \sim N(y_{ij} - \mathbf{x_i^{N_j}}\boldsymbol{\beta} - \frac{\sigma^2_{u_j}}{\lambda_j}, \sigma^2_{u_j})\mathrm{I}(v_{ij} > 0)$, where $i = K_{j-1} + 1, ..., K_j$ is the bank-year index, $j = 1, ..., 14$ is the country's index, $\mathbf{v_j} = (v_{K_{j-1}+1}, ..., v_{K_j})^T$ is the $N_j \times 1$ inefficiency vector for country j, $\mathbf{x_i^{N_j}}$ is the i's row of the X matrix (only the observations for country j) and $\mathrm{I}(v_{ij}) > 0$ is an indicator function that takes the value one if $v_{ij} > 0$ and zero otherwise.

For all the results reported in this study we used 5,000 burn in samples and 55,000 Markov Chain Monte Carlo iterations. As a start up values, we use a vector of relatively small inefficiency parameters: $\mathbf{v^{[0]}} = [0.05\ 0.05\ ...\ 0.05]^T$, where $\mathbf{v}$ is of dimension $N \times 1$ and low ${\sigma^2_{u_j}}^{[0]} = 0.01$.

6.3 Empirical Results

By estimating country specific efficiency relative to a common frontier, the results become comparable and an argument can be made on whether the higher efficiency nations might take advantage of the single market regulatory uniformization process to expand their operations across borders.

We start the discussion of the results with a look at the technology parameters and economies of scale, leaving the efficiency analysis at the end.

Tables 6.1 through 6.7 report the posterior means and standard deviation together with the 90 percent highest density regions for the translog parameters obtained under the assumption of common frontier (M2 or the first approach as identified by Berger, 2007) in contrast to the pooled frontier and the country specific frontiers (M1, chapter 5).

[6]following Jondrow at al.(1983)

Table 6.1: Translog Parameters: Posterior Means and Standard Deviation , 90% H.D.R.*

Parameters	M_2°	M_1◊ pooled	CROATIA	DENMARK
β_1	1.4410	1.4610	1.8180	1.8810
Post. S.D.	(0.0234)	(0.0193)	(0.5494)	(0.2251)
$[H.D.R.]$	[1.4030 , 1.4800]	[1.4290 , 1.4930]	[0.9074 , 2.7080]	[1.5010 , 2.2390]
β_2	0.4431	0.2800	-0.4263	-0.1706
Post. S.D.	(0.0192)	(0.0106)	(0.4902)	(0.1928)
$[H.D.R.]$	[0.4112 , 0.4745]	[0.2626 , 0.2975]	[-1.2420 , 0.3747]	[-0.4807 , 0.1521]
β_3	0.0542	0.0846	0.1572	0.1198
Post. S.D.	(0.0047)	(0.0029)	(0.1232)	(0.0404)
$[H.D.R.]$	[0.0465 , 0.0620]	[0.0798 , 0.0894]	[-0.0456 , 0.3592]	[0.0521 , 0.1845]
β_4	0.4753	0.3882	0.3659	0.1363
Post. S.D.	(0.0118)	(0.0104)	(0.6233)	(0.1369)
$[H.D.R.]$	[0.4559 , 0.4948]	[0.3711 , 0.4053]	[-0.6483 , 1.3970]	[-0.0847 , 0.3645]
β_5	0.0478	0.0609	0.1287	-0.0370
Post. S.D.	(0.0020)	(0.0020)	(0.1815)	(0.0281)
$[H.D.R.]$	[0.0446 , 0.0511]	[0.0576 , 0.0641]	[-0.1708 , 0.4235]	[-0.0831 , 0.0091]
β_6	0.3536	0.2668	0.7201	0.5137
Post. S.D.	(0.0087)	(0.0071)	(0.1331)	(0.0921)
$[H.D.R.]$	[0.3395 , 0.3681]	[0.2552 , 0.2785]	[0.5004 , 0.9384]	[0.3632 , 0.6670]
β_7	0.0269	0.0361	0.1043	0.0333
Post. S.D.	(0.0010)	(0.0008)	(0.0186)	(0.0104)
$[H.D.R.]$	[0.0253 , 0.0284]	[0.0347 , 0.0374]	[0.0737 , 0.1347]	[0.0160 , 0.0503]
β_8	-0.0856	-0.0553	0.4844	0.3231
Post. S.D.	(0.0057)	(0.0047)	(0.2693)	(0.0653)
$[H.D.R.]$	[-0.0950 , -0.0762]	[-0.0632 , -0.0476]	[0.0419 , 0.9305]	[0.2152 , 0.4290]
β_9	-0.0555	-0.0150	-0.1049	-0.1264
Post. S.D.	(0.0041)	(0.0032)	(0.0789)	(0.0348)
$[H.D.R.]$	[-0.0622 , -0.0488]	[-0.0203 , -0.0097]	[-0.2340 , 0.0248]	[-0.1836 , -0.0689]
β_{10}	-0.0540	-0.0144	-0.3116	-0.1019
Post. S.D.	(0.0029)	(0.0024)	(0.0864)	(0.0340)
$[H.D.R.]$	[-0.0588 , -0.0493]	[-0.0184 , -0.0104]	[-0.4532 , -0.1693]	[-0.1582 , -0.0468]
Obs.	13970	13970	121	375
No. banks	2819	2819	26	78

Notes: * Highest Density Region
◊ The results were obtained in the previous chapter using the pooled database , assuming common frontier (model M_1).
○ The results were obtained using a multiple lambda model (common frontier , allowing for the inefficiencies to differ for each country - model M_2).
Posterior moments are computed based on 50,000 points generated from the Gibbs sampling algorithm. The end points of the 90% confidence region are the 5^{th} and the 95^{th} percentiles of the posterior marginal densities.

Table 6.2: Translog Parameters: Posterior Means and Standard Deviation , 90% H.D.R.*

Parameters	$M_2{}^{\circ}$	$M_1{}^{\Diamond}$ pooled	FRANCE	GERMANY
β_1	1.4410	1.4610	-0.5787	1.3770
Post. S.D.	(0.0234)	(0.0193)	(0.1357)	(0.0286)
$[H.D.R.]$	[1.4030 , 1.4800]	[1.4290 , 1.4930]	[-0.7989 , -0.3537]	[1.3300 , 1.4240]
β_2	0.4431	0.2800	1.8690	0.5245
Post. S.D.	(0.0192)	(0.0106)	(0.1120)	(0.0271)
$[H.D.R.]$	[0.4112 , 0.4745]	[0.2626 , 0.2975]	[1.6850 , 2.0520]	[0.4801 , 0.5693]
β_3	0.0542	0.0846	-0.1508	-0.0133
Post. S.D.	(0.0047)	(0.0029)	(0.0244)	(0.0082)
$[H.D.R.]$	[0.0465 , 0.0620]	[0.0798 , 0.0894]	[-0.1911 , -0.1108]	[-0.0268 , 0.0002]
β_4	0.4753	0.3882	1.2550	0.5231
Post. S.D.	(0.0118)	(0.0104)	(0.0855)	(0.0135)
$[H.D.R.]$	[0.4559 , 0.4948]	[0.3711 , 0.4053]	[1.1130 , 1.3960]	[0.5012 , 0.5455]
β_5	0.0478	0.0609	-0.0019	0.0486
Post. S.D.	(0.0020)	(0.0020)	(0.0175)	(0.0022)
$[H.D.R.]$	[0.0446 , 0.0511]	[0.0576 , 0.0641]	[-0.0310 , 0.0269]	[0.0449 , 0.0521]
β_6	0.3536	0.2668	0.2237	0.4973
Post. S.D.	(0.0087)	(0.0071)	(0.0366)	(0.0133)
$[H.D.R.]$	[0.3395 , 0.3681]	[0.2552 , 0.2785]	[0.1638 , 0.2839]	[0.4755 , 0.5192]
β_7	0.0269	0.0361	0.0104	0.0298
Post. S.D.	(0.0010)	(0.0008)	(0.0033)	(0.0014)
$[H.D.R.]$	[0.0253 , 0.0284]	[0.0347 , 0.0374]	[0.0049 , 0.0156]	[0.0275 , 0.0321]
β_8	-0.0856	-0.0553	-0.5363	-0.0780
Post. S.D.	(0.0057)	(0.0047)	(0.0353)	(0.0076)
$[H.D.R.]$	[-0.0950 , -0.0762]	[-0.0632 , -0.0476]	[-0.5939 , -0.4779]	[-0.0906 , -0.0654]
β_9	-0.0555	-0.0150	-0.0062	-0.0745
Post. S.D.	(0.0041)	(0.0032)	(0.0131)	(0.0073)
$[H.D.R.]$	[-0.0622 , -0.0488]	[-0.0203 , -0.0097]	[-0.0278 , 0.0156]	[-0.0865 , -0.0625]
β_{10}	-0.0540	-0.0144	-0.0795	-0.1276
Post. S.D.	(0.0029)	(0.0024)	(0.0134)	(0.0048)
$[H.D.R.]$	[-0.0588 , -0.0493]	[-0.0184 , -0.0104]	[-0.1016 , -0.0577]	[-0.1354 , -0.1197]
Obs.	13970	13970	527	8668
No. banks	2819	2819	171	1471

Notes: $*$ Highest Density Region
$\Diamond$ The results were obtained in the previous chapter using the pooled database , assuming common frontier (model M_1).
$\circ$ The results were obtained using a multiple lambda model (common frontier , allowing for the inefficiencies to differ for each country - model M_2).
Posterior moments are computed based on 50,000 points generated from the Gibbs sampling algorithm. The end points of the 90% confidence region are the 5^{th} and the 95^{th} percentiles of the posterior marginal densities.

Table 6.3: Translog Parameters: Posterior Means and Standard Deviation , 90% H.D.R.*

Parameters	M_2°	$M_1^{\lozenge}$ pooled	ITALY	NETHERLANDS
β_1	1.4410	1.4610	0.6475	1.9450
Post. S.D.	(0.0234)	(0.0193)	(0.0776)	(0.2310)
$[H.D.R.]$	[1.4030 , 1.4800]	[1.4290 , 1.4930]	[0.5165 , 0.7708]	[1.5550 , 2.3130]
β_2	0.4431	0.2800	0.6200	0.5145
Post. S.D.	(0.0192)	(0.0106)	(0.0733)	(0.1627)
$[H.D.R.]$	[0.4112 , 0.4745]	[0.2626 , 0.2975]	[0.5021 , 0.7420]	[0.2479 , 0.7837]
β_3	0.0542	0.0846	0.0789	-0.0226
Post. S.D.	(0.0047)	(0.0029)	(0.0206)	(0.0600)
$[H.D.R.]$	[0.0465 , 0.0620]	[0.0798 , 0.0894]	[0.0447 , 0.1125]	[-0.1226 , 0.0747]
β_4	0.4753	0.3882	0.2138	-0.0437
Post. S.D.	(0.0118)	(0.0104)	(0.0433)	(0.1077)
$[H.D.R.]$	[0.4559 , 0.4948]	[0.3711 , 0.4053]	[0.1453 , 0.2879]	[-0.2196 , 0.1357]
β_5	0.0478	0.0609	0.1272	0.0840
Post. S.D.	(0.0020)	(0.0020)	(0.0065)	(0.0187)
$[H.D.R.]$	[0.0446 , 0.0511]	[0.0576 , 0.0641]	[0.1163 , 0.1375]	[0.0527 , 0.1144]
β_6	0.3536	0.2668	0.3584	-0.1013
Post. S.D.	(0.0087)	(0.0071)	(0.0286)	(0.0996)
$[H.D.R.]$	[0.3395 , 0.3681]	[0.2552 , 0.2785]	[0.3112 , 0.4054]	[-0.2663 , 0.0627]
β_7	0.0269	0.0361	0.0252	0.0090
Post. S.D.	(0.0010)	(0.0008)	(0.0028)	(0.0186)
$[H.D.R.]$	[0.0253 , 0.0284]	[0.0347 , 0.0374]	[0.0206 , 0.0298]	[-0.0218 , 0.0391]
β_8	-0.0856	-0.0553	0.0929	-0.0266
Post. S.D.	(0.0057)	(0.0047)	(0.0240)	(0.0511)
$[H.D.R.]$	[-0.0950 , -0.0762]	[-0.0632 , -0.0476]	[0.0529 , 0.1315]	[-0.1099 , 0.0585]
β_9	-0.0555	-0.0150	-0.0453	0.0998
Post. S.D.	(0.0041)	(0.0032)	(0.0116)	(0.0462)
$[H.D.R.]$	[-0.0622 , -0.0488]	[-0.0203 , -0.0097]	[-0.0644 , -0.0262]	[0.0234 , 0.1755]
β_{10}	-0.0540	-0.0144	-0.0772	0.0312
Post. S.D.	(0.0029)	(0.0024)	(0.0097)	(0.0346)
$[H.D.R.]$	[-0.0588 , -0.0493]	[-0.0184 , -0.0104]	[-0.0931 , -0.0611]	[-0.0262 , 0.0876]
Obs.	13970	13970	1818	134
No. banks	2819	2819	561	36

Notes: ∗ Highest Density Region
◊ The results were obtained in the previous chapter using the pooled database , assuming common frontier (model M_1).
○ The results were obtained using a multiple lambda model (common frontier , allowing for the inefficiencies to differ for each country - model M_2).
Posterior moments are computed based on 50,000 points generated from the Gibbs sampling algorithm. The end points of the 90% confidence region are the 5^{th} and the 95^{th} percentiles of the posterior marginal densities.

Table 6.4: Translog Parameters: Posterior Means and Standard Deviation , 90% H.D.R.*

Parameters	M_2°	M_1◊ pooled	POLAND	ROMANIA
β_1	1.4410	1.4610	1.2580	2.3330
Post. S.D.	(0.0234)	(0.0193)	(0.3549)	(0.1742)
$[H.D.R.]$	[1.4030 , 1.4800]	[1.4290 , 1.4930]	[0.6735 , 1.8410]	[2.0440 , 2.6160]
β_2	0.4431	0.2800	-0.2465	0.0511
Post. S.D.	(0.0192)	(0.0106)	(0.1380)	(0.1946)
$[H.D.R.]$	[0.4112 , 0.4745]	[0.2626 , 0.2975]	[-0.4733 , -0.0191]	[-0.2701 , 0.3711]
β_3	0.0542	0.0846	-0.0062	-0.0260
Post. S.D.	(0.0047)	(0.0029)	(0.0288)	(0.0558)
$[H.D.R.]$	[0.0465 , 0.0620]	[0.0798 , 0.0894]	[-0.0536 , 0.0407]	[-0.1190 , 0.0662]
β_4	0.4753	0.3882	1.5740	0.3902
Post. S.D.	(0.0118)	(0.0104)	(0.4274)	(0.1263)
$[H.D.R.]$	[0.4559 , 0.4948]	[0.3711 , 0.4053]	[0.8706 , 2.2720]	[0.1893 , 0.6026]
β_5	0.0478	0.0609	-0.3970	0.0400
Post. S.D.	(0.0020)	(0.0020)	(0.1306)	(0.0542)
$[H.D.R.]$	[0.0446 , 0.0511]	[0.0576 , 0.0641]	[-0.6095 , -0.1823]	[-0.0500 , 0.1277]
β_6	0.3536	0.2668	0.1195	0.2221
Post. S.D.	(0.0087)	(0.0071)	(0.1268)	(0.0972)
$[H.D.R.]$	[0.3395 , 0.3681]	[0.2552 , 0.2785]	[-0.0881 , 0.3269]	[0.0609 , 0.3809]
β_7	0.0269	0.0361	0.0236	0.0149
Post. S.D.	(0.0010)	(0.0008)	(0.0161)	(0.0127)
$[H.D.R.]$	[0.0253 , 0.0284]	[0.0347 , 0.0374]	[-0.0028 , 0.0502]	[-0.0060 , 0.0357]
β_8	-0.0856	-0.0553	0.2495	0.1920
Post. S.D.	(0.0057)	(0.0047)	(0.0688)	(0.0881)
$[H.D.R.]$	[-0.0950 , -0.0762]	[-0.0632 , -0.0476]	[0.1357 , 0.3625]	[0.0476 , 0.3366]
β_9	-0.0555	-0.0150	-0.0230	0.0059
Post. S.D.	(0.0041)	(0.0032)	(0.0445)	(0.0401)
$[H.D.R.]$	[-0.0622 , -0.0488]	[-0.0203 , -0.0097]	[-0.0964 , 0.0501]	[-0.0594 , 0.0722]
β_{10}	-0.0540	-0.0144	0.0581	-0.0685
Post. S.D.	(0.0029)	(0.0024)	(0.0697)	(0.0453)
$[H.D.R.]$	[-0.0588 , -0.0493]	[-0.0184 , -0.0104]	[-0.0555 , 0.1729]	[-0.1427 , 0.0062]
Obs.	13970	13970	93	104
No. banks	2819	2819	28	23

Notes: ∗ Highest Density Region
◊ The results were obtained in the previous chapter using the pooled database , assuming common frontier (model M_1).
∘ The results were obtained using a multiple lambda model (common frontier , allowing for the inefficiencies to differ for each country - model M_2).
Posterior moments are computed based on 50,000 points generated from the Gibbs sampling algorithm. The end points of the 90% confidence region are the 5^{th} and the 95^{th} percentiles of the posterior marginal densities.

Table 6.5: Translog Parameters: Posterior Means and Standard Deviation , 90% H.D.R.*

Parameters	$M_2{}^{\circ}$	$M_1{}^{\Diamond}$ pooled	SERBIA	SLOVENIA
β_1	1.4410	1.4610	2.9580	0.6707
Post. S.D.	(0.0234)	(0.0193)	(0.4669)	(0.3750)
$[H.D.R.]$	[1.4030 , 1.4800]	[1.4290 , 1.4930]	[2.2190 , 3.7500]	[0.0551 , 1.2820]
β_2	0.4431	0.2800	1.0940	-0.1811
Post. S.D.	(0.0192)	(0.0106)	(0.3519)	(0.3340)
$[H.D.R.]$	[0.4112 , 0.4745]	[0.2626 , 0.2975]	[0.4963 , 1.6450]	[-0.7262 , 0.3687]
β_3	0.0542	0.0846	0.0342	0.2513
Post. S.D.	(0.0047)	(0.0029)	(0.1216)	(0.1121)
$[H.D.R.]$	[0.0465 , 0.0620]	[0.0798 , 0.0894]	[-0.1823 , 0.2126]	[0.0668 , 0.4333]
β_4	0.4753	0.3882	0.1938	1.3100
Post. S.D.	(0.0118)	(0.0104)	(0.3922)	(0.3892)
$[H.D.R.]$	[0.4559 , 0.4948]	[0.3711 , 0.4053]	[-0.4239 , 0.8529]	[0.6691 , 1.9480]
β_5	0.0478	0.0609	0.0533	-0.1808
Post. S.D.	(0.0020)	(0.0020)	(0.1419)	(0.1091)
$[H.D.R.]$	[0.0446 , 0.0511]	[0.0576 , 0.0641]	[-0.1911 , 0.2741]	[-0.3599 , -0.0019]
β_6	0.3536	0.2668	0.2612	-0.0111
Post. S.D.	(0.0087)	(0.0071)	(0.1681)	(0.2938)
$[H.D.R.]$	[0.3395 , 0.3681]	[0.2552 , 0.2785]	[-0.0024 , 0.5469]	[-0.4900 , 0.4710]
β_7	0.0269	0.0361	0.0203	0.2864
Post. S.D.	(0.0010)	(0.0008)	(0.0169)	(0.0793)
$[H.D.R.]$	[0.0253 , 0.0284]	[0.0347 , 0.0374]	[-0.0061 , 0.0495]	[0.1561 , 0.4173]
β_8	-0.0856	-0.0553	-0.1436	0.0378
Post. S.D.	(0.0057)	(0.0047)	(0.2447)	(0.1714)
$[H.D.R.]$	[-0.0950 , -0.0762]	[-0.0632 , -0.0476]	[-0.5399 , 0.2611]	[-0.2435 , 0.3205]
β_9	-0.0555	-0.0150	0.0115	0.2618
Post. S.D.	(0.0041)	(0.0032)	(0.0620)	(0.1604)
$[H.D.R.]$	[-0.0622 , -0.0488]	[-0.0203 , -0.0097]	[-0.0887 , 0.1142]	[-0.0026 , 0.5253]
β_{10}	-0.0540	-0.0144	-0.0438	-0.1004
Post. S.D.	(0.0029)	(0.0024)	(0.0667)	(0.1691)
$[H.D.R.]$	[-0.0588 , -0.0493]	[-0.0184 , -0.0104]	[-0.1511 , 0.0673]	[-0.3773 , 0.1784]
Obs.	13970	13970	80	84
No. banks	2819	2819	25	17

Notes: $*$ Highest Density Region
$\Diamond$ The results were obtained in the previous chapter using the pooled database , assuming common frontier (model M_1).
$\circ$ The results were obtained using a multiple lambda model (common frontier , allowing for the inefficiencies to differ for each country - model M_2).
Posterior moments are computed based on 50,000 points generated from the Gibbs sampling algorithm. The end points of the 90% confidence region are the 5^{th} and the 95^{th} percentiles of the posterior marginal densities.

Table 6.6: Translog Parameters: Posterior Means and Standard Deviation , 90% H.D.R.*

Parameters	M_2°	M_1◊ pooled	SWEDEN	SWITZERLAND
β_1	1.4410	1.4610	0.2531	0.9185
Post. S.D.	(0.0234)	(0.0193)	(0.4173)	(0.1169)
$[H.D.R.]$	[1.4030 , 1.4800]	[1.4290 , 1.4930]	[-0.4380 , 0.9333]	[0.7281 , 1.1130]
β_2	0.4431	0.2800	-0.5513	0.1686
Post. S.D.	(0.0192)	(0.0106)	(0.2126)	(0.0652)
$[H.D.R.]$	[0.4112 , 0.4745]	[0.2626 , 0.2975]	[-0.8991 , -0.1966]	[0.0622 , 0.2766]
β_3	0.0542	0.0846	0.2098	0.1287
Post. S.D.	(0.0047)	(0.0029)	(0.0417)	(0.0115)
$[H.D.R.]$	[0.0465 , 0.0620]	[0.0798 , 0.0894]	[0.1407 , 0.2780]	[0.1098 , 0.1476]
β_4	0.4753	0.3882	2.2810	0.3592
Post. S.D.	(0.0118)	(0.0104)	(0.3713)	(0.0516)
$[H.D.R.]$	[0.4559 , 0.4948]	[0.3711 , 0.4053]	[1.6730 , 2.8930]	[0.2741 , 0.4441]
β_5	0.0478	0.0609	-0.5057	0.0520
Post. S.D.	(0.0020)	(0.0020)	(0.0844)	(0.0058)
$[H.D.R.]$	[0.0446 , 0.0511]	[0.0576 , 0.0641]	[-0.6447 , -0.3684]	[0.0422 , 0.0615]
β_6	0.3536	0.2668	0.2813	0.1464
Post. S.D.	(0.0087)	(0.0071)	(0.0799)	(0.0399)
$[H.D.R.]$	[0.3395 , 0.3681]	[0.2552 , 0.2785]	[0.1507 , 0.4133]	[0.0816 , 0.2125]
β_7	0.0269	0.0361	0.0238	-0.0052
Post. S.D.	(0.0010)	(0.0008)	(0.0043)	(0.0027)
$[H.D.R.]$	[0.0253 , 0.0284]	[0.0347 , 0.0374]	[0.0166 , 0.0309]	[-0.0096 , -0.0009]
β_8	-0.0856	-0.0553	0.2042	-0.0222
Post. S.D.	(0.0057)	(0.0047)	(0.0753)	(0.0184)
$[H.D.R.]$	[-0.0950 , -0.0762]	[-0.0632 , -0.0476]	[0.0798 , 0.3282]	[-0.0527 , 0.0081]
β_9	-0.0555	-0.0150	0.0429	-0.0049
Post. S.D.	(0.0041)	(0.0032)	(0.0187)	(0.0177)
$[H.D.R.]$	[-0.0622 , -0.0488]	[-0.0203 , -0.0097]	[0.0121 , 0.0736]	[-0.0341 , 0.0242]
β_{10}	-0.0540	-0.0144	-0.1121	-0.0730
Post. S.D.	(0.0029)	(0.0024)	(0.0323)	(0.0085)
$[H.D.R.]$	[-0.0588 , -0.0493]	[-0.0184 , -0.0104]	[-0.1656 , -0.0591]	[-0.0870 , -0.0591]
Obs.	13970	13970	344	1188
No. banks	2819	2819	61	221

Notes: * Highest Density Region
◊ The results were obtained in the previous chapter using the pooled database , assuming common frontier (model M_1).
○ The results were obtained using a multiple lambda model (common frontier , allowing for the inefficiencies to differ for each country - model M_2).
Posterior moments are computed based on 50,000 points generated from the Gibbs sampling algorithm. The end points of the 90% confidence region are the 5^{th} and the 95^{th} percentiles of the posterior marginal densities.

Table 6.7: Translog Parameters: Posterior Means and Standard Deviation , 90% H.D.R.*

Parameters	$M_2{}^{\circ}$	$M_1{}^{\Diamond}$ pooled	TURKEY	UNITED KINGDOM
β_1	1.4410	1.4610	1.4140	1.5440
Post. S.D.	(0.0234)	(0.0193)	(0.1965)	(0.1427)
$[H.D.R.]$	[1.4030 , 1.4800]	[1.4290 , 1.4930]	[1.0990 , 1.7460]	[1.2830 , 1.7520]
β_2	0.4431	0.2800	0.3001	0.3522
Post. S.D.	(0.0192)	(0.0106)	(0.2443)	(0.0836)
$[H.D.R.]$	[0.4112 , 0.4745]	[0.2626 , 0.2975]	[-0.1021 , 0.7007]	[0.2165 , 0.4907]
β_3	0.0542	0.0846	0.2389	-0.0085
Post. S.D.	(0.0047)	(0.0029)	(0.0995)	(0.0266)
$[H.D.R.]$	[0.0465 , 0.0620]	[0.0798 , 0.0894]	[0.0754 , 0.4024]	[-0.0537 , 0.0333]
β_4	0.4753	0.3882	0.6709	0.2576
Post. S.D.	(0.0118)	(0.0104)	(0.1959)	(0.0415)
$[H.D.R.]$	[0.4559 , 0.4948]	[0.3711 , 0.4053]	[0.3388 , 0.9804]	[0.1900 , 0.3264]
β_5	0.0478	0.0609	0.0487	0.0623
Post. S.D.	(0.0020)	(0.0020)	(0.0600)	(0.0135)
$[H.D.R.]$	[0.0446 , 0.0511]	[0.0576 , 0.0641]	[-0.0500 , 0.1475]	[0.0402 , 0.0844]
β_6	0.3536	0.2668	0.0724	0.3191
Post. S.D.	(0.0087)	(0.0071)	(0.2163)	(0.0444)
$[H.D.R.]$	[0.3395 , 0.3681]	[0.2552 , 0.2785]	[-0.2826 , 0.4293]	[0.2461 , 0.3918]
β_7	0.0269	0.0361	-0.0198	0.0211
Post. S.D.	(0.0010)	(0.0008)	(0.0699)	(0.0058)
$[H.D.R.]$	[0.0253 , 0.0284]	[0.0347 , 0.0374]	[-0.1352 , 0.0946]	[0.0115 , 0.0307]
β_8	-0.0856	-0.0553	0.3035	0.0615
Post. S.D.	(0.0057)	(0.0047)	(0.1216)	(0.0280)
$[H.D.R.]$	[-0.0950 , -0.0762]	[-0.0632 , -0.0476]	[0.0990 , 0.5002]	[0.0158 , 0.1077]
β_9	-0.0555	-0.0150	-0.1627	-0.1003
Post. S.D.	(0.0041)	(0.0032)	(0.1590)	(0.0250)
$[H.D.R.]$	[-0.0622 , -0.0488]	[-0.0203 , -0.0097]	[-0.4262 , 0.0981]	[-0.1411 , -0.0591]
β_{10}	-0.0540	-0.0144	-0.0650	-0.0711
Post. S.D.	(0.0029)	(0.0024)	(0.1225)	(0.0171)
$[H.D.R.]$	[-0.0588 , -0.0493]	[-0.0184 , -0.0104]	[-0.2635 , 0.1381]	[-0.0991 , -0.0429]
Obs.	13970	13970	84	350
No. banks	2819	2819	18	85

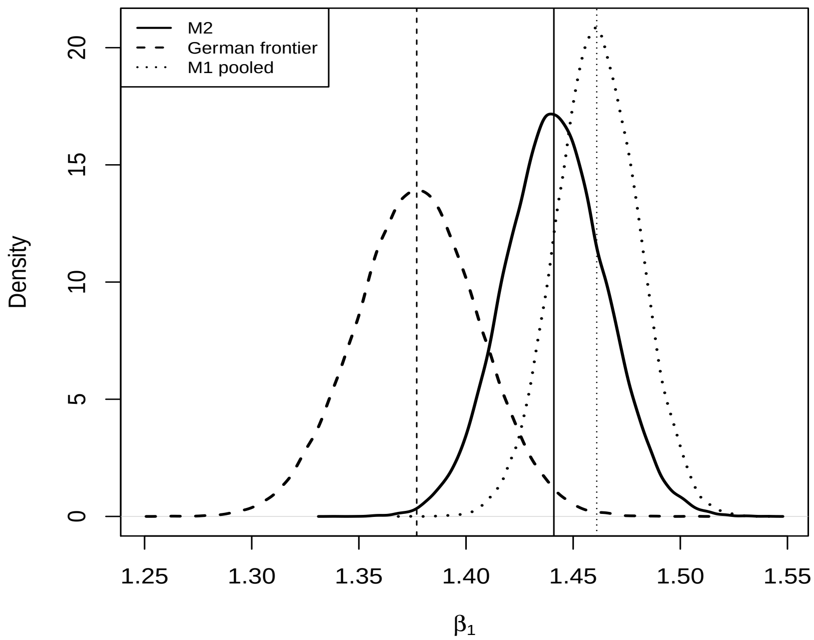
Notes: * Highest Density Region
◊ The results were obtained in the previous chapter using the pooled database , assuming common frontier (model M_1).
∘ The results were obtained using a multiple lambda model (common frontier , allowing for the inefficiencies to differ for each country - model M_2).
Posterior moments are computed based on 50,000 points generated from the Gibbs sampling algorithm. The end points of the 90% confidence region are the 5^{th} and the 95^{th} percentiles of the posterior marginal densities.

As noted in the previous chapter's results, we observe, as expected, larger values for the posterior means of the translog parameters that correspond to the linear terms of the cost function and lower values for the quadratic and interaction terms. While we expect the technology of the common frontier (M2) to be different than the national frontiers, we also point out that there are differences from the pooled frontier. This is not surprising since the common frontier in this chapter and the pooled frontier in chapter 5 correspond to different statistical models. To estimate the common frontier this time we employ a model with unequal variances and we allow each country to individually deviate from the single frontier (we have 14 σ^2 and 14 λ parameters), while the pooled frontier does not take into account the heterogeneity of the groups (one σ^2 and one λ).

To visualize these differences, we plot the posterior marginal densities for β's drawn for the German frontier (M1), the pooled frontier (M1 pooled) and the common frontier (M2). Figures 6.1 through 6.5 are a good illustration of the fact that the results for the technology parameters are not exclusively driven by Germany as the country with half of the sample's observations and that taking into account the heterogeneity of the data (multiple λ's and σ^2 instead of one each) affects the technology. For a complete image of how technologies vary, we also add Figure 6.6 in which frontiers are drawn for the pooled frontier, the common frontier and the German frontier while holding loan/equity and security/equity variables constant at the median values of the pooled dataset, as the avwage/avrate varies between its minimum and maximum values. Both common and pooled frontiers visibly violate the concavity property of the cost function.

Based on the common frontier technology, we examine the previously selected groups of banks (small, medium and large) and again investigate the economies of scale. The results are reported in tables 6.8 through 6.10. They include the posterior means, standard deviation and 90 percent highest density regions for the economies of scale calculated based on the common frontier's technology.

Germany



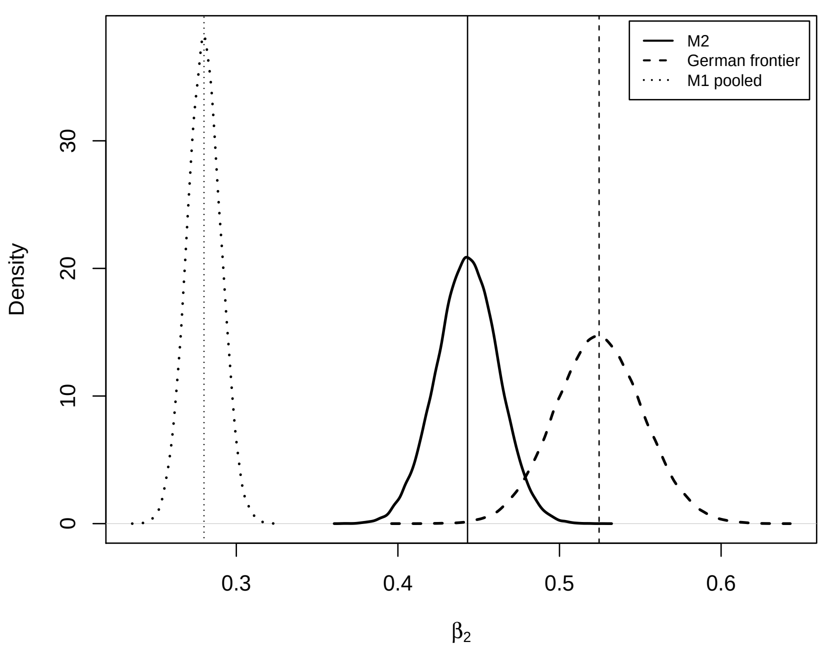


Figure 6.1: Posterior Marginal Densities for Translog Parameters β_1 and β_2 - Germany.

Germany

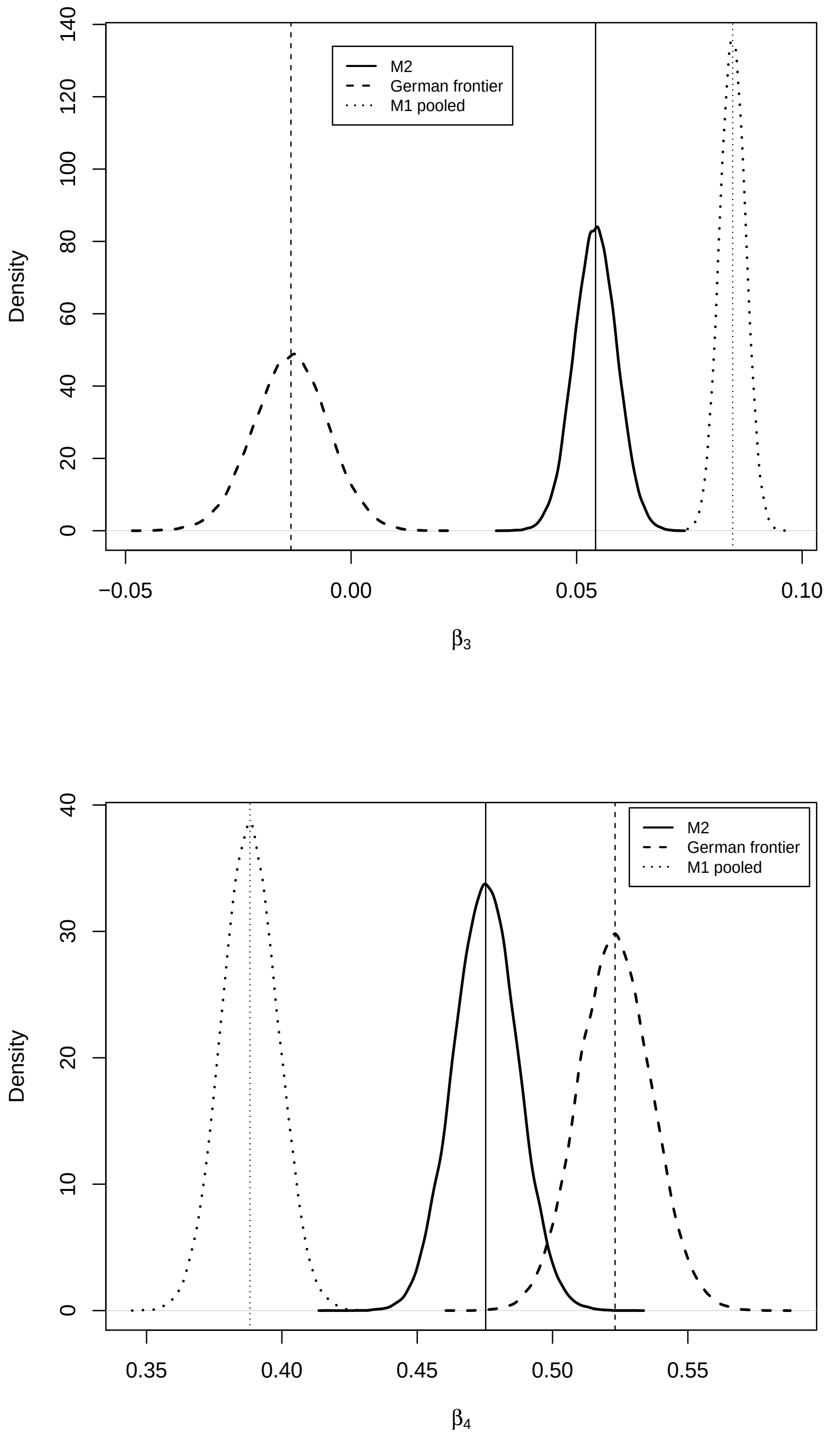
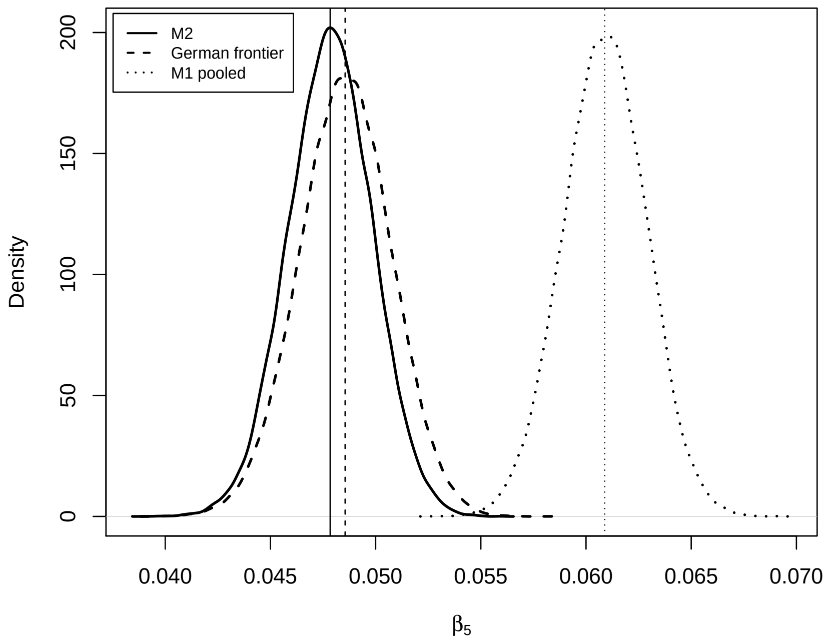


Figure 6.2: Posterior Marginal Densities for Translog Parameters β_3 and β_4 - Germany.

Germany



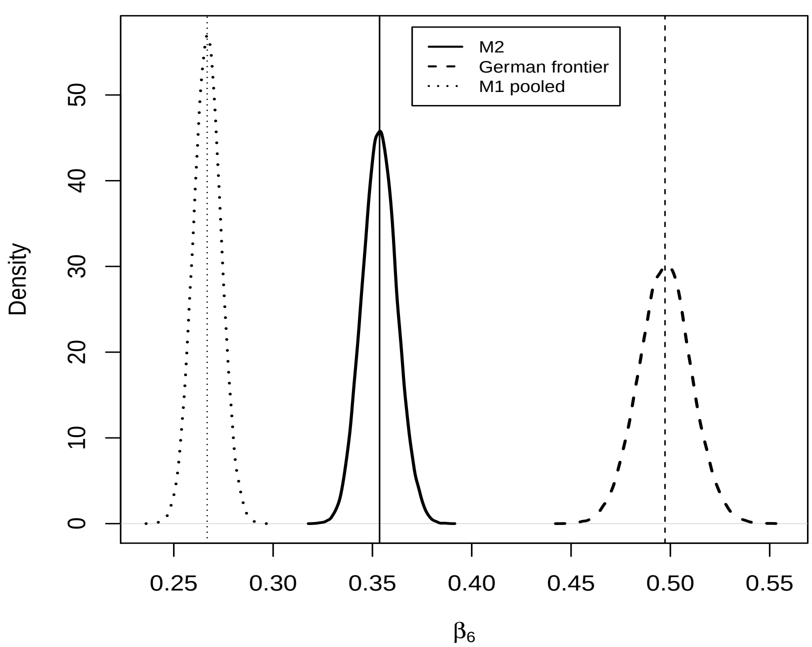


Figure 6.3: Posterior Marginal Densities for Translog Parameters β_5 and β_6 - Germany.

Germany

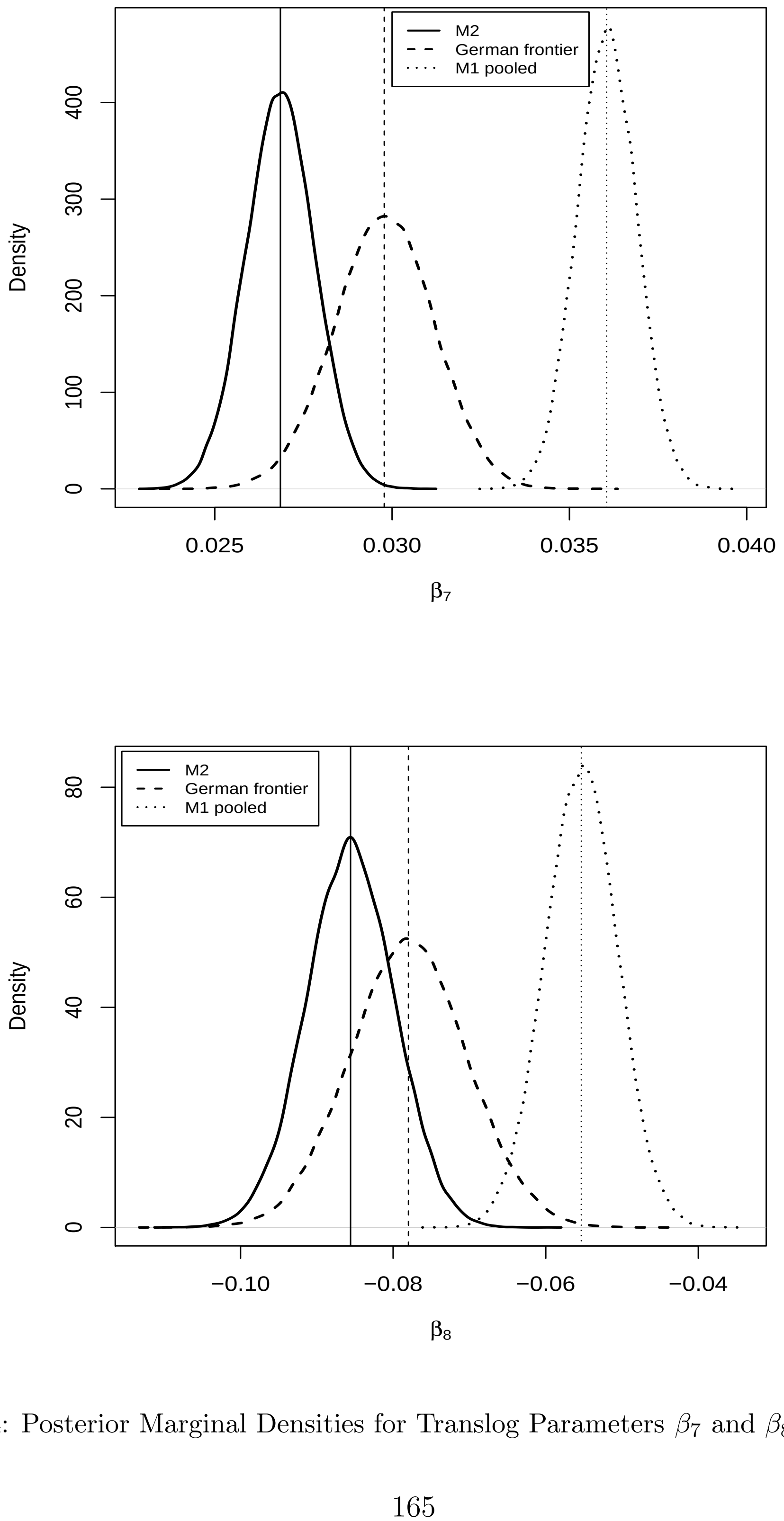


Figure 6.4: Posterior Marginal Densities for Translog Parameters β_7 and β_8 - Germany.

Germany

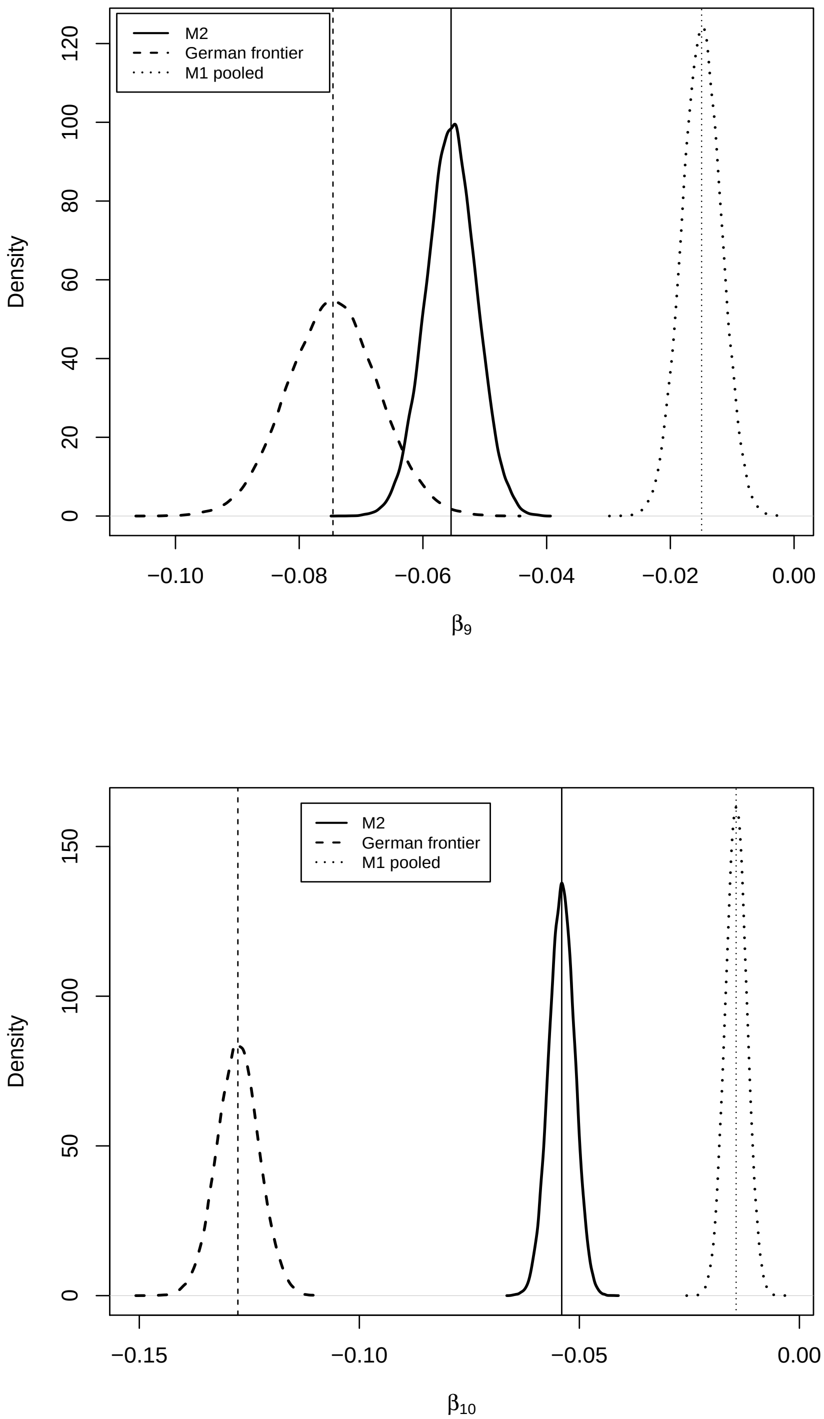


Figure 6.5: Posterior Marginal Densities for Translog Parameters β_9 and β_{10} - Germany.

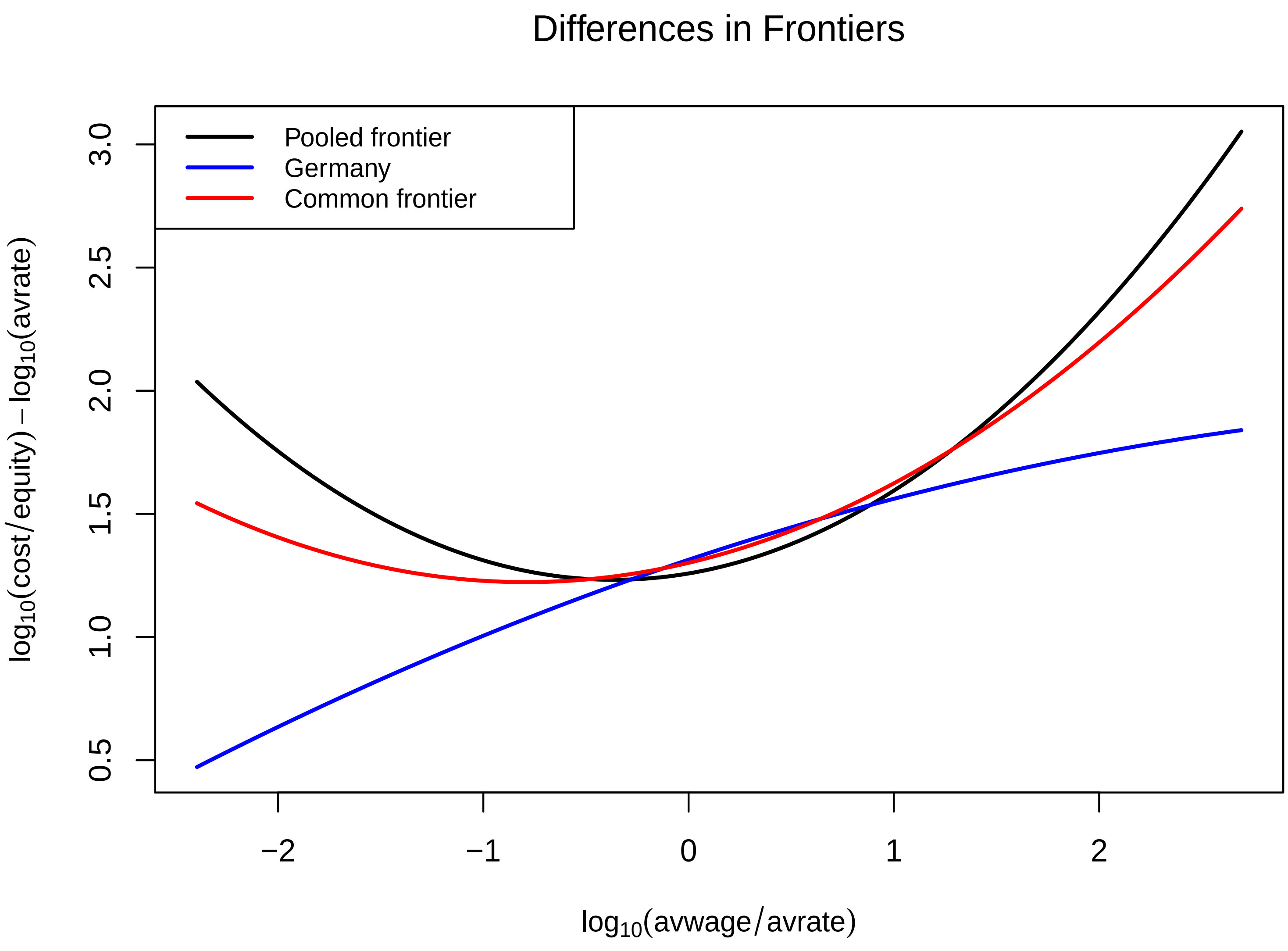


Figure 6.6: Pooled, German and Common Frontiers Drawn at the Sample Median Values for loan/equity and security/equity.

All the small banks (Table 6.8) with the exception of the Romanian bank (Romanian International Bank) exhibit increasing economies of scale and could reduce their costs by increasing the output as the posterior means for the economies of scale range from 1.10 for the Serbian bank (Cacanska Banka) to 1.68 for the Italian cooperative bank (Banca di Credito Cooperativo di Nettuno). For the Romanian bank (Romanian International Bank), the posterior mean is 1.01 and the HDR includes one, suggesting constant returns.

The economies of scale estimates for most small banks remain close to the pooled frontier results from chapter 5. There are significant changes in the case of the German, French and Italian banks for which the posterior means of the economies of scale increase and for the Croatian, Romanian and Serbian bank for which the economies of scale decrease.

Among the medium banks (Table 6.9), the Romanian (Intesa Sanpaolo Romania, 0.98) and the Serbian bank (Volksbank, 1.03) exhibit constant returns, as the highest density regions includes one. Very close to constant returns is also the Turkish Bank with posterior mean of the economies of scale at 1.06 and highest density region of $[1.02, 1.09]$. All the other medium banks selected could reduce their costs by expanding the output, the posterior means of the economies of scale ranging from 1.10 for the Croatian bank (Medimurska banka) to 1.61 for the Swiss bank (Alternative Bank ABS). When comparing these results against the chapter 5 estimates based on the pooled frontier, we observe that for 13 out of the 16 banks, there are significant changes. The economies of scale of the Danish (Froes Herreds Sparekasse), German, Slovenian, Swiss and British banks increase when computed against the common frontier instead of the pooled, while for the Croatian, Romanian, Serbian, Swedish and Turkish banks they decrease.

As economies of scale are a nonlinear function of most of the technology parameters (β_4 through β_{10}), the differences that we obtain in the economies of scale estimates against the pooled versus the common frontier, further illustrate the idea that the two frontiers are not the same.

Table 6.8: Economies of Scale$^{\diamond}$ for Selected Banks (Small): Posterior Means, Standard Deviation, and 90% H.D.R.*

Bank name	Country	Specialization	Total assets	Post. mean	Post. S.D.	*H.D.R.**
Partner Banka dd	HR	Commercial Bank	252.39	1.14	0.01	[1.12 , 1.16]
Lollands Bank	DK	Commercial Bank	311.47	1.41	0.01	[1.39 , 1.43]
Sparekassen i Skals	DK	Savings Bank	269.60	1.42	0.01	[1.40 , 1.45]
Banque Pouyanne	FR	Commercial Bank	301.49	1.44	0.02	[1.42 , 1.47]
Volksbank Sandhofen eG	DE	Cooperative bank	301.63	1.30	0.01	[1.28 , 1.32]
Sparkasse Froendenberg	DE	Savings Bank	309.73	1.26	0.02	[1.24 , 1.29]
Bankhaus Ludwig Sperrer	DE	Commercial Bank	289.56	1.29	0.01	[1.27 , 1.31]
Banca di Credito Cooperativo di Nettuno	IT	Cooperative Bank	258.94	1.68	0.02	[1.64 , 1.72]
Romanian International Bank SA	RO	Commercial Bank	202.80	1.01	0.02	[0.97 , 1.05]
Cacanska Banka AD, Cacak	RS	Commercial Bank	260.62	1.10	0.02	[1.06 , 1.13]
Södra Hestra Sparbank	SE	Savings Bank	257.34	1.48	0.02	[1.45 , 1.51]
Vimmerby Sparbank AB	SE	Commercial Bank	181.49	1.49	0.02	[1.45 , 1.53]
GRB Glarner Regionalbank	CH	Commercial Bank	296.76	1.48	0.02	[1.44 , 1.52]
Reliance Bank Limited	UK	Commercial Bank	368.12	1.24	0.01	[1.23 , 1.26]

Notes: $\diamond$ Based on common frontier (M2).
$*$ Highest Density Region.
Posterior moments are computed based on 50,000 points generated from the Gibbs sampling algorithm. The end points of the 90% confidence region are the 5^{th} and the 95^{th} percentiles of the posterior marginal densities.

Table 6.9: Economies of Scale◊ for Selected Banks (Medium): Posterior Means, Standard Deviation, and 90% H.D.R.*

Bank name	Country	Specialization	Total assets	Post. mean	Post. S.D.	*H.D.R.**
Medimurska banka dd	HR	Commercial Bank	534.82	1.10	0.01	[1.08 , 1.12]
Froes Herreds Sparekasse	DK	Savings Bank	691.59	1.45	0.01	[1.42 , 1.47]
Morsoe Bank	DK	Commercial Bank	714.60	1.30	0.01	[1.28 , 1.32]
Banque Chalus	FR	Commercial Bank	760.19	1.31	0.01	[1.29 , 1.33]
Raiffeisenbank Straubing eG	DE	Cooperative bank	702.64	1.32	0.01	[1.30 , 1.35]
Sparkasse Mecklenburg-Strelitz	DE	Savings Bank	722.36	1.23	0.02	[1.21 , 1.26]
Frankfurter Bankgesellschaft AG	DE	Commercial Bank	562.49	1.47	0.02	[1.44 , 1.50]
Cassa rurale di Tuenno	IT	Cooperative Bank	680.70	1.23	0.01	[1.22 , 1.25]
Intesa Sanpaolo Romania SA	RO	Commercial Bank	729.28	0.98	0.02	[0.95 , 1.00]
Volksbank ad	RS	Commercial Bank	986.23	1.03	0.02	[0.99 , 1.07]
Postna Banka Slovenije dd	SI	Commercial Bank	921.97	1.23	0.02	[1.20 , 1.26]
Sparbanken Lidköping AB	SE	Commercial Bank	664.95	1.48	0.02	[1.45 , 1.52]
Roslagens Sparbank Roslagsbanken	SE	Savings Bank	683.14	1.51	0.03	[1.47 , 1.55]
Alternative Bank ABS	CH	Commercial Bank	686.45	1.61	0.03	[1.56 , 1.66]
Turkish Bank A.S.	TR	Commercial Bank	650.28	1.06	0.02	[1.02 , 1.09]
Arbuthnot Latham & Co. Ltd.	UK	Commercial Bank	619.52	1.37	0.01	[1.35 , 1.39]

Notes: ◊ Based on common frontier (M2).
∗ Highest Density Region.
Posterior moments are computed based on 50,000 points generated from the Gibbs sampling algorithm. The end points of the 90% confidence region are the 5^{th} and the 95^{th} percentiles of the posterior marginal densities.

Table 6.10: Economies of Scale$^{\diamond}$ for Selected Banks (Large): Posterior Means, Standard Deviation, and 90% H.D.R.*

Bank name	Country	Specialization	Total assets	Post. mean	Post. S.D.	*H.D.R.**
Hrvatska Postanska Bank DD	HR	Commercial	2920.69	1.13	0.01	[1.12 , 1.15]
Skandinaviska Enskilda Banken A/S	DK	Commercial	2770.29	1.79	0.03	[1.73 , 1.84]
Banque Populaire des Alpes	FR	Cooperative	10741.06	1.34	0.02	[1.30 , 1.38]
Société Bordelaise de Crédit Ind. et Comm.	FR	Commercial	8894.45	1.13	0.02	[1.09 , 1.17]
Kreissparkasse Limburg	DE	Savings	2119.09	1.21	0.01	[1.18 , 1.23]
Hamburger Volksbank eG	DE	Cooperative	2134.40	1.40	0.02	[1.37 , 1.42]
Thüringer Aufbaubank	DE	Commercial	2660.68	1.14	0.01	[1.12 , 1.16]
Banca Padovana Credito Cooperativo SC	IT	Cooperative	3232.59	1.24	0.01	[1.22 , 1.25]
Cassa di risparmio di Alessandria SpA	IT	Savings	3381.27	1.30	0.01	[1.28 , 1.32]
Banca Monte Parma SpA	IT	Commercial	3477.11	1.25	0.01	[1.23 , 1.27]
Staalbankiers NV	NL	Commercial	4380.10	1.42	0.02	[1.39 , 1.45]
Bank BPH SA	PL	Commercial	5347.76	1.29	0.01	[1.27 , 1.31]
Banca Romaneasca S.A.	RO	Commercial	2776.87	1.04	0.02	[1.01 , 1.06]
AIK Banka ad Nis	RS	Commercial	1457.16	1.04	0.02	[1.01 , 1.08]
Gorenjska Banka d.d. Kranj	SI	Commercial	2551.01	1.23	0.01	[1.21 , 1.25]
Färs & Frosta Sparbank AB	SE	Commercial	1702.99	1.47	0.02	[1.44 , 1.50]
ABN Amro Bank (Schweiz) AG	CH	Commercial	3294.00	1.56	0.02	[1.53 , 1.58]
Anadolubank A.S.	TR	Commercial	2702.80	0.95	0.01	[0.92 , 0.97]
JP Morgan International Bank Ltd	UK	Commercial	7361.90	1.62	0.03	[1.57 , 1.68]

Notes: $\diamond$ Based on common frontier (M2).
$*$ Highest Density Region.
Posterior moments are computed based on 50,000 points generated from the Gibbs sampling algorithm. The end points of the 90% confidence region are the 5^{th} and the 95^{th} percentiles of the posterior marginal densities.

The large bank results (Table 6.10) show that the majority of them would benefit from increasing the output (posterior means for economies of scale being greater than one with the exception of Turkey). None of the highest density regions includes one.

The selected banks have posterior means of economies of scale that range from 1.04 for the Romanian (Banca Romaneasca) and Serbian (AIK Banka ad Nis, we observe that only for 5 banks the posterior means remain close in values when calculated based on the common frontier. For 7 banks (German, Dutch, Swiss, British and the Italian commercial bank), the economies of scale increase, while for the other remaining 7 banks, the economies of scale decrease when calculated against the common frontier.

As a visual presentation of the economies of scale for the large banks, we include the plots of their smoothed posterior marginal densities (figures 6.7 through 6.20). The posterior marginal densities are drawn for the common and the pooled frontiers side by side for comparison and reference.

Though in this model we allow for heterogeneity in the data, in a statistical model with fourteen λ's and fourteen σ^2's, the technology parameters are estimated based on the pooled dataset ($N = 13,970$ observations) and as in the case of the pooled frontier, this leads to mostly symmetric posterior marginal densities for the large banks' economies of scale.

After looking at the technology parameters, we switch the discussion to the efficiency estimates and report the results for λ (Table 6.11), the efficiency score (6.12) and σ^2 (Table 6.13). The tables contain the posterior means, standard deviations and highest density regions computed based on 50,000 points generated from the Gibbs sampling algorithm. We include for comparisons the posterior means of the same parameters obtained in chapter 5 under the individual country frontier assumption.

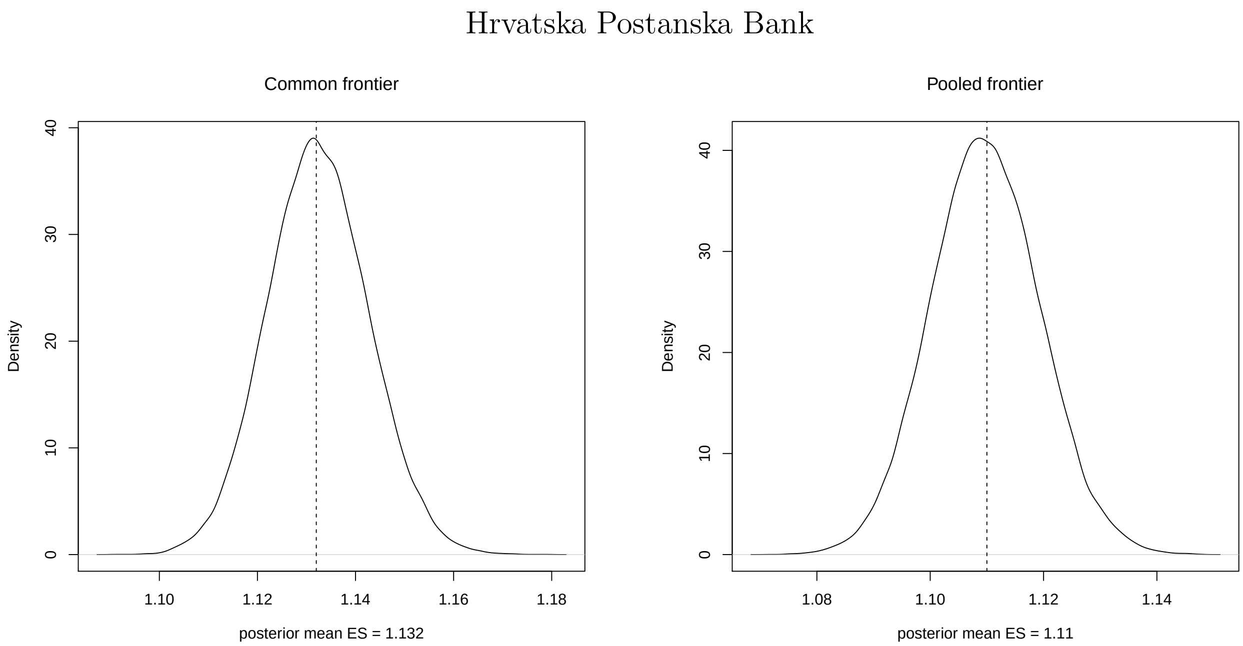


Figure 6.7: Croatia - Posterior Marginal Density for Economies of Scale, Large Bank.

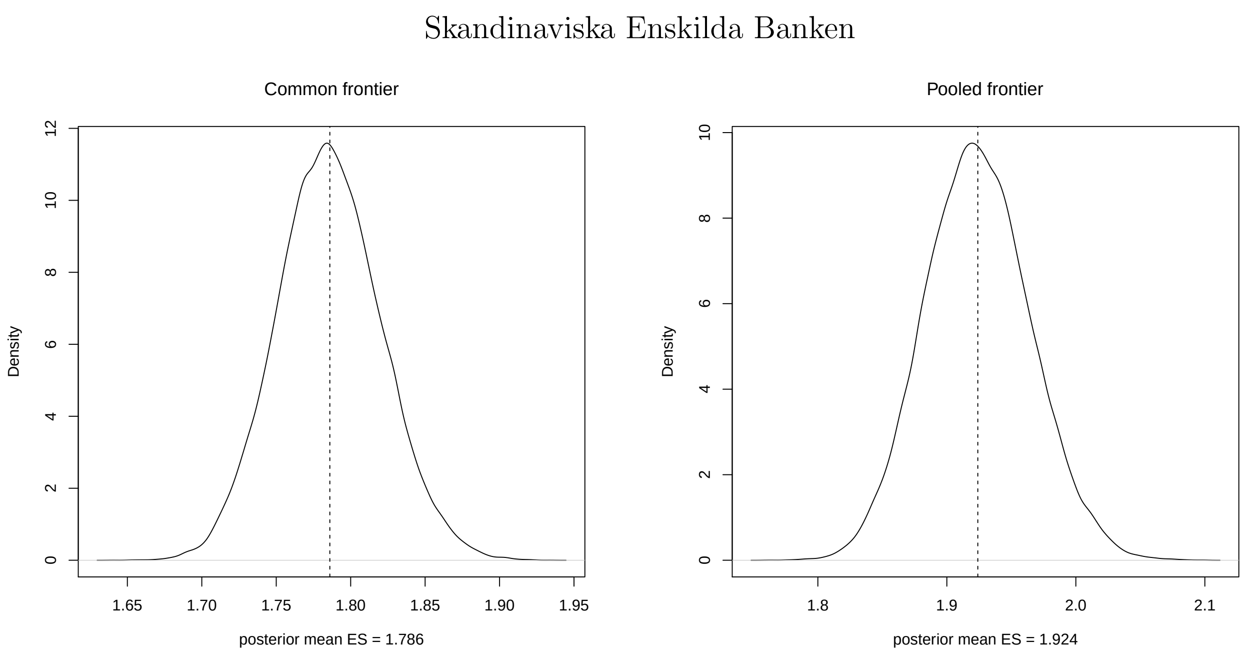


Figure 6.8: Denmark - Posterior Marginal Density for Economies of Scale, Large Bank.

Société Bordelaise de Crédit Industriel et Commercial

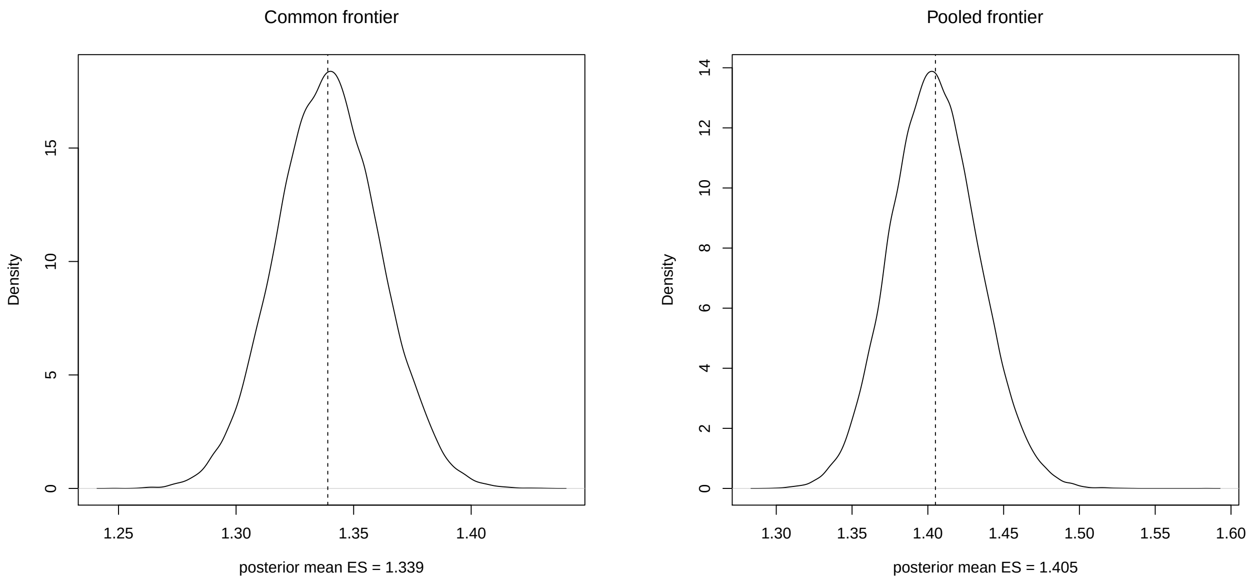


Figure 6.9: France - Posterior Marginal Density for Economies of Scale, Large Bank.

Thüringer Aufbaubank

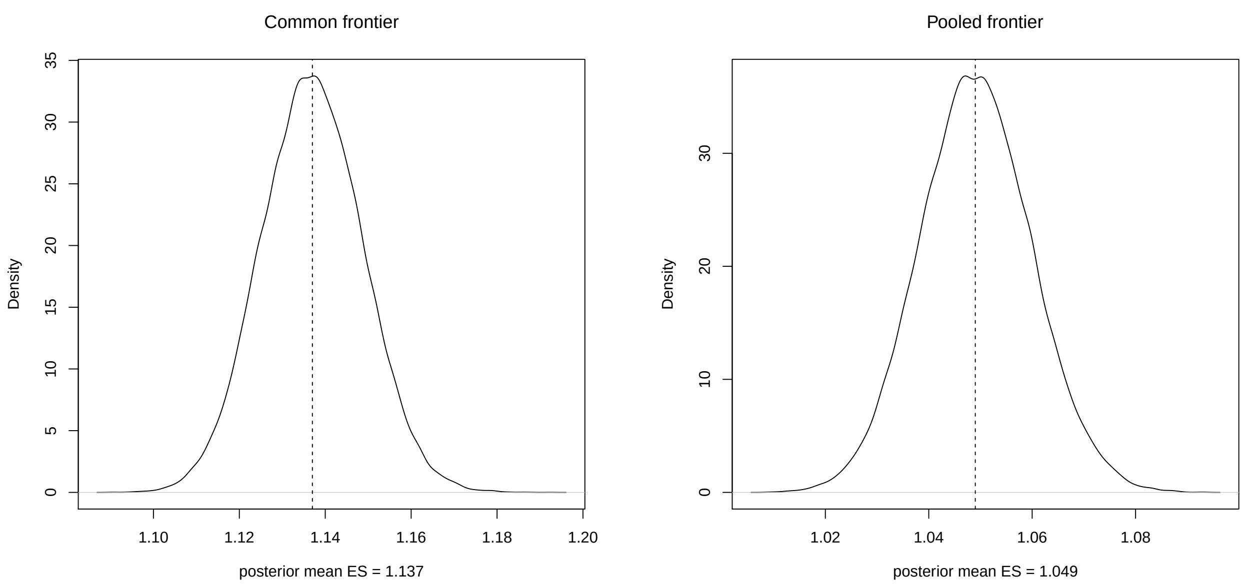


Figure 6.10: Germany - Posterior Marginal Density for Economies of Scale, Large Bank.

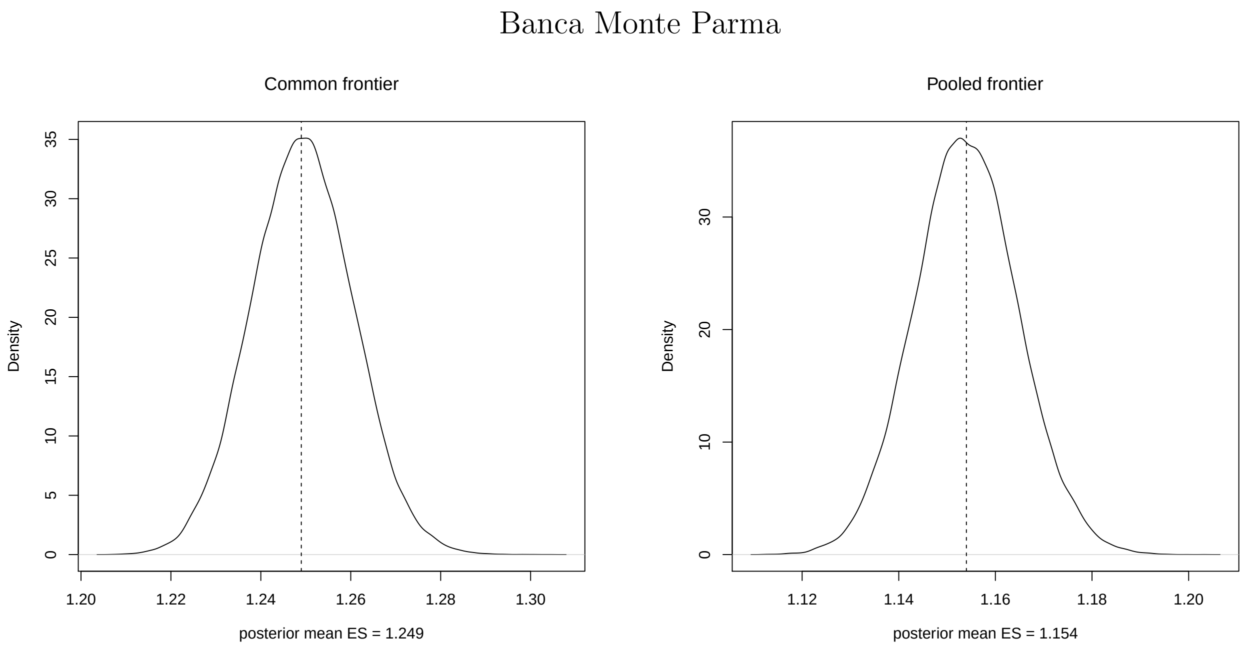


Figure 6.11: Italy - Posterior Marginal Density for Economies of Scale, Large Bank.

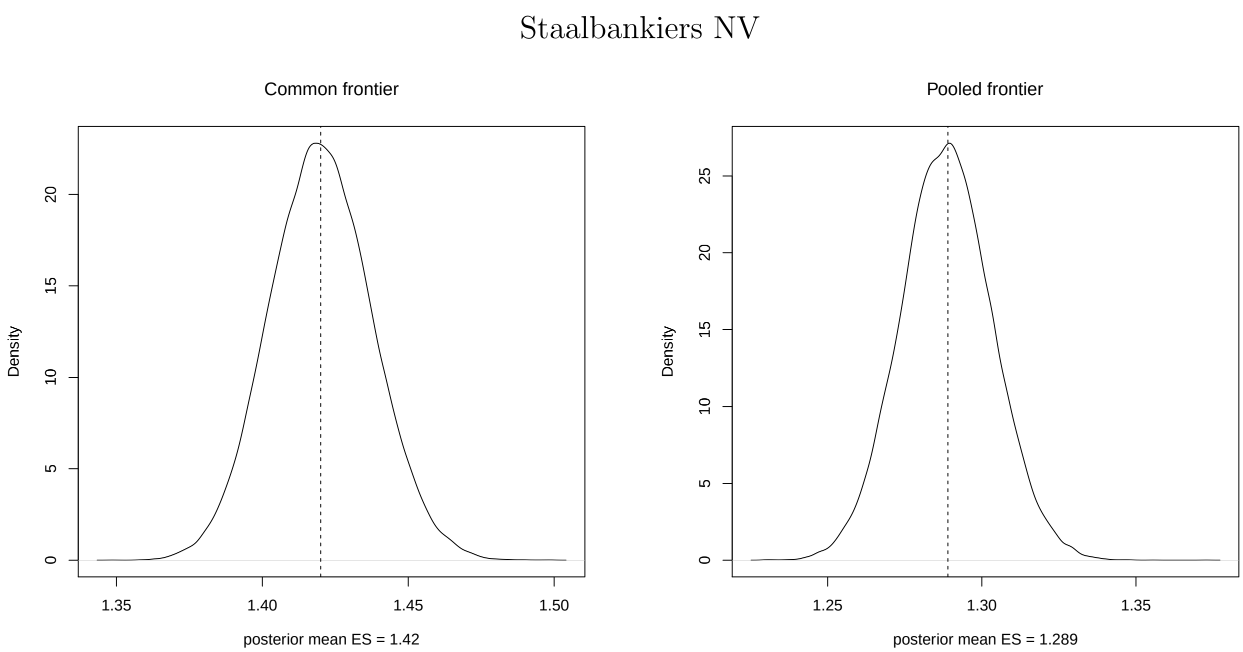


Figure 6.12: Netherlands - Posterior Marginal Density for Economies of Scale, Large Bank.

Bank BPH

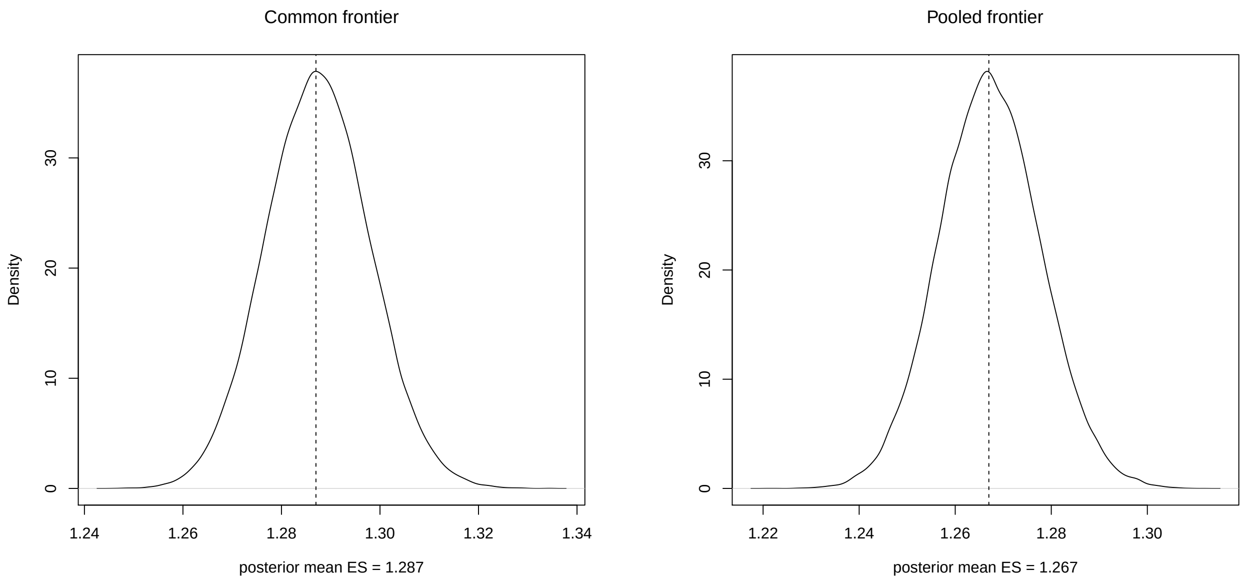


Figure 6.13: Poland - Posterior Marginal Density for Economies of Scale, Large Bank.

Banca Romaneasca

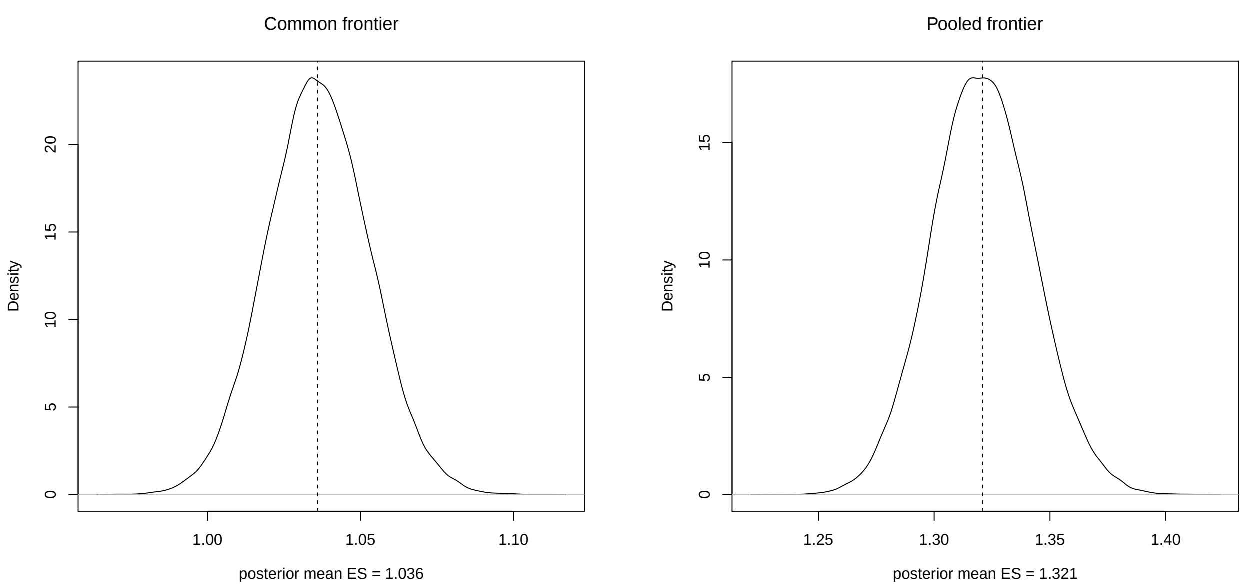


Figure 6.14: Romania - Posterior Marginal Density for Economies of Scale, Large Bank.

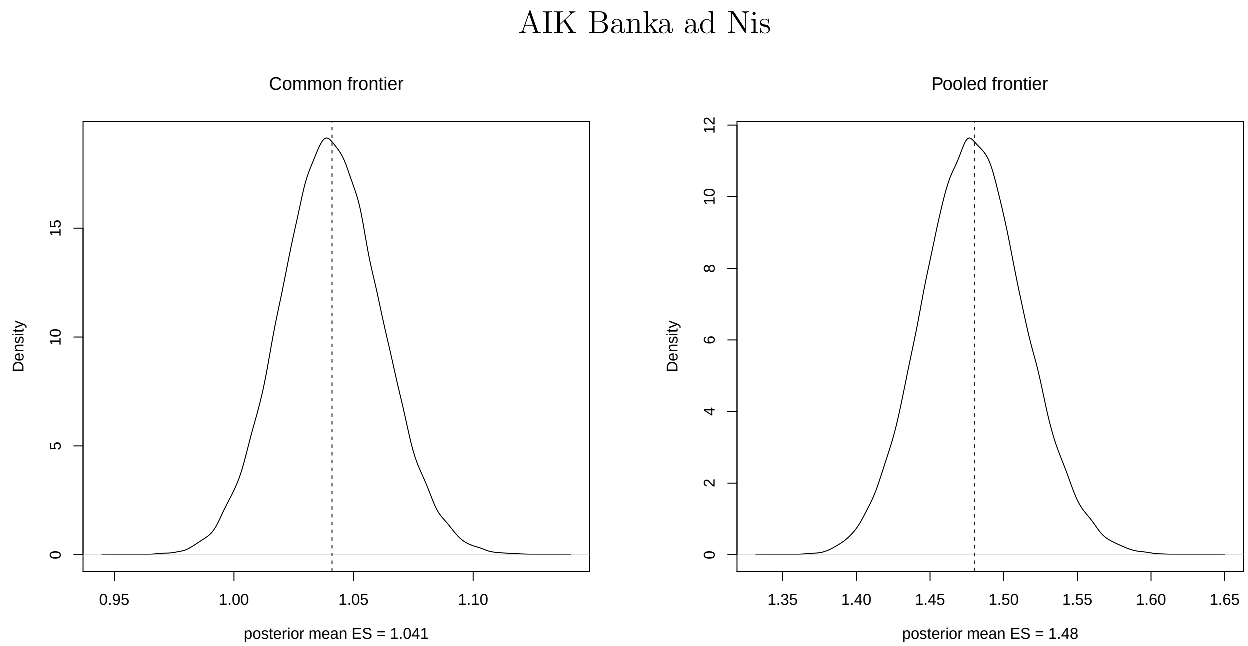


Figure 6.15: Serbia - Posterior Marginal Density for Economies of Scale, Large Bank.

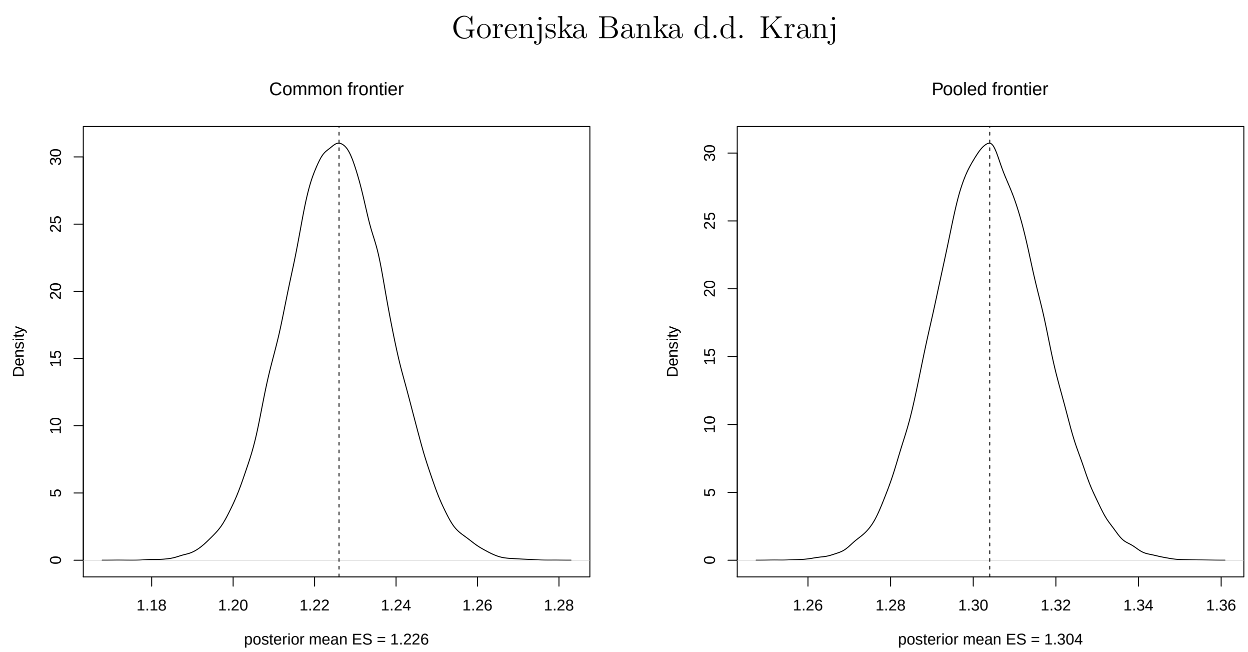


Figure 6.16: Slovenia - Posterior Marginal Density for Economies of Scale, Large Bank.

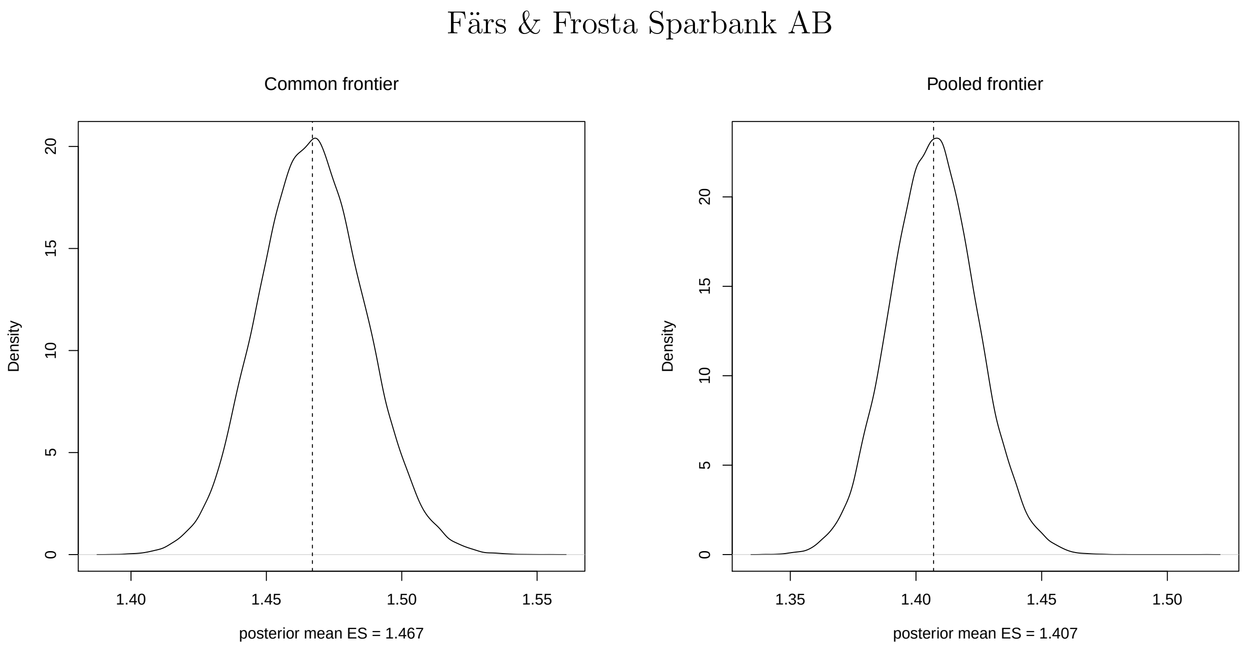


Figure 6.17: Sweden - Posterior Marginal Density for Economies of Scale, Large Bank.

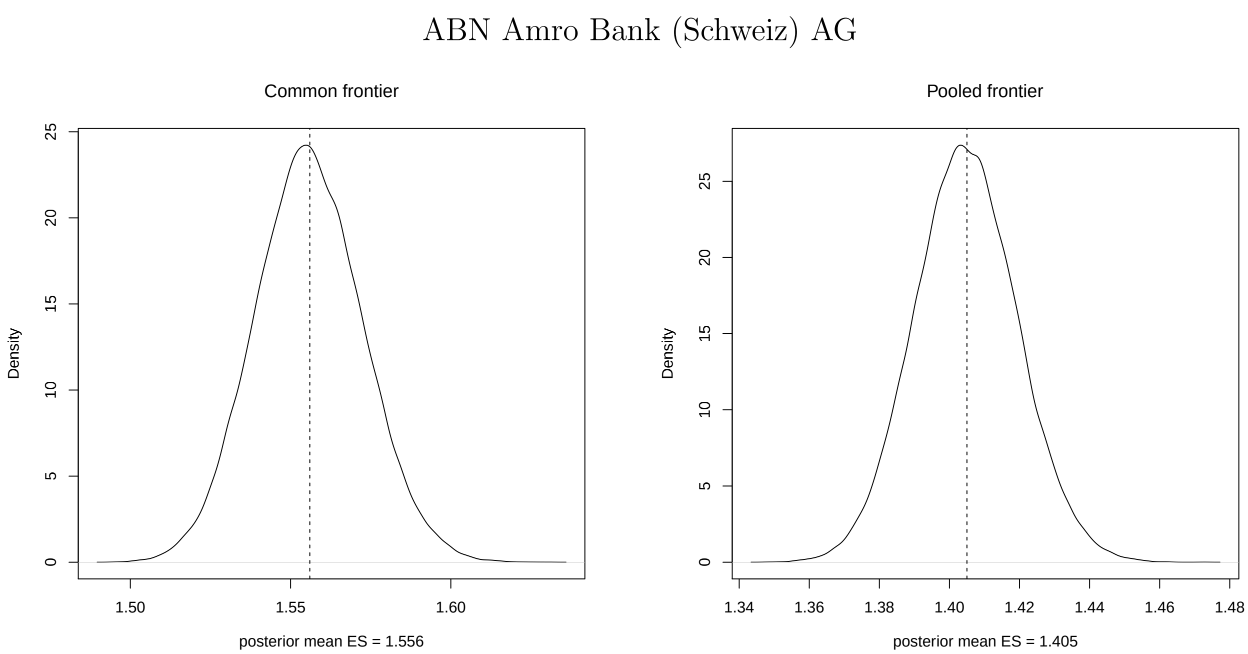


Figure 6.18: Switzerland - Posterior Marginal Density for Economies of Scale, Large Bank.

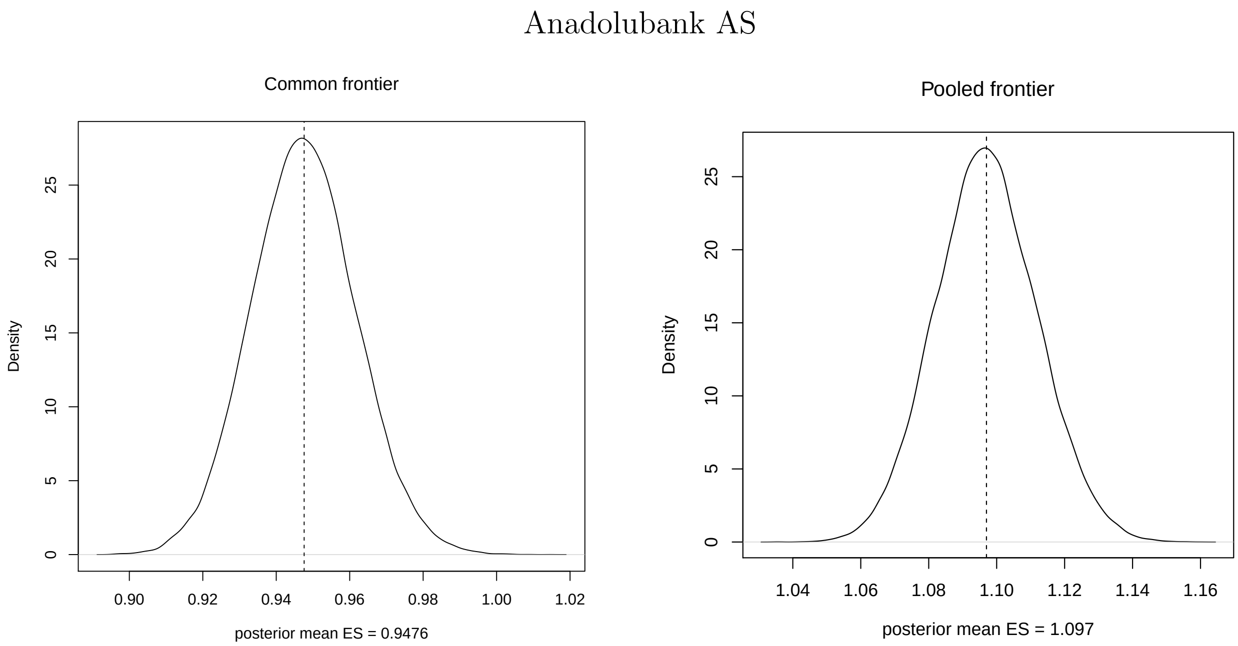


Figure 6.19: Turkey - Posterior Marginal Density for Economies of Scale, Large Bank.

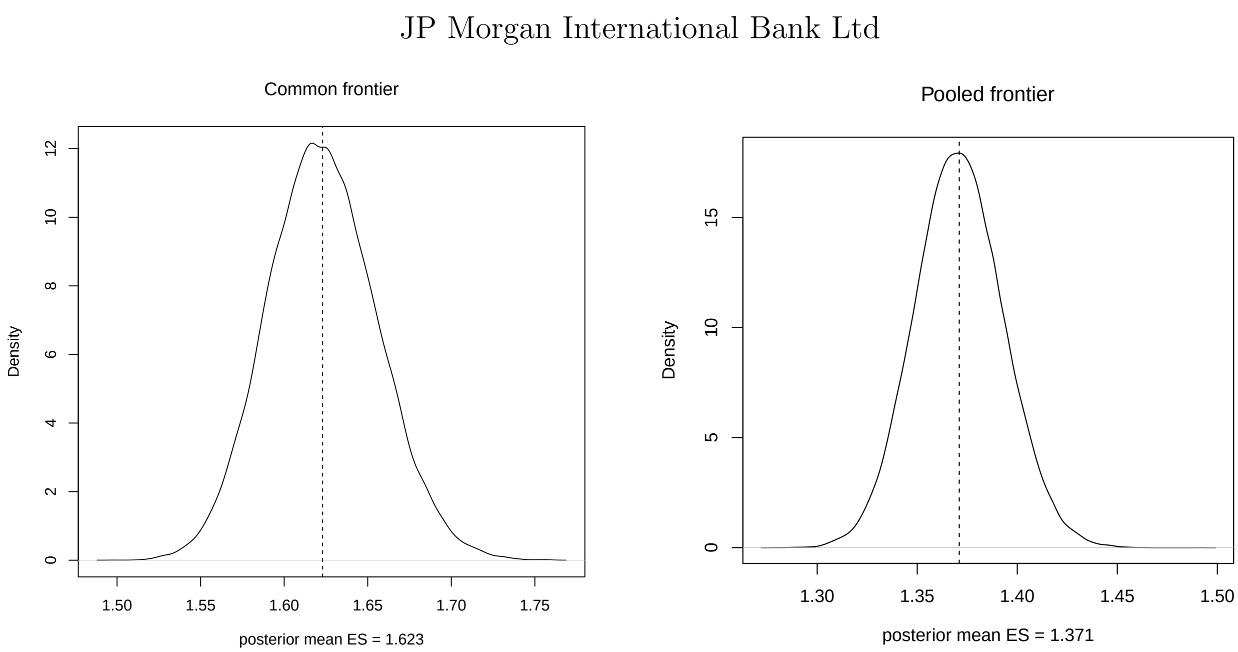


Figure 6.20: United Kingdom - Posterior Marginal Density for Economies of Scale, Large Bank.

Table 6.11: λ - Posterior Means and Standard Deviation , 90% H.D.R.*

Country name	Obs.	No. banks	λ M_1 ◊	λ M_2 ∘	Post. S.D. M_2 ∘	H.D.R. M_2 ∘
CROATIA	121	26	0.1090	0.5641	0.0620	[0.4670 , 0.6707]
DENMARK	375	78	0.1899	0.0320	0.0104	[0.0176 , 0.0509]
FRANCE	527	171	0.4078	0.0396	0.0132	[0.0209 , 0.0639]
GERMANY	8668	1471	0.1601	0.1749	0.0038	[0.1687 , 0.1811]
ITALY	1818	561	0.2168	0.0081	0.0014	[0.0059 , 0.0106]
NETHERLANDS	134	36	0.2002	0.0508	0.0222	[0.0231 , 0.0929]
POLAND	93	28	0.0916	0.2278	0.0629	[0.1252 , 0.3338]
ROMANIA	104	23	0.1598	0.9437	0.1143	[0.7659 , 1.1410]
SERBIA	80	25	0.5139	1.4210	0.1916	[1.1250 , 1.7550]
SLOVENIA	84	17	0.0851	0.0445	0.0171	[0.0218 , 0.0767]
SWEDEN	344	61	0.1408	0.0286	0.0087	[0.0163 , 0.0447]
SWITZERLAND	1188	221	0.5112	0.0152	0.0036	[0.0100 , 0.0216]
TURKEY	84	18	0.1863	0.2221	0.0458	[0.1485 , 0.2965]
UNITED KINGDOM	350	85	0.1653	0.0502	0.0196	[0.0245 , 0.0874]

Notes:
∗ Highest Density Region
◊ The results were obtained in the previous chapter using individual frontiers for each country (model M_1).
∘ The results were obtained using a multiple lambda model (common frontier, allowing for the inefficiencies to differ for each country - model M_2).
Posterior moments are computed based on 50,000 points generated from the Gibbs sampling algorithm. The end points of the 90% confidence region are the 5^{th} and the 95^{th} percentiles of the posterior marginal densities.

Dramatic decreases in efficiency are observed in the case of Croatia (as $\bar{\lambda}$ increases from 0.109 to 0.564, $\bar{r}$ - the mean efficiency score decreases from 89.79 percent to 57 percent), Romania (as $\bar{\lambda}$ increases from 0.16 to 0.94, $\bar{r}$ decreases from 85.5 percent to 39.17 percent) and Serbia (while it remains the least efficient, $\bar{\lambda}$ increases from 0.51 to 1.42, its $\bar{r}$ decreasing from 60.28 to 24.59 percent). A more moderate decrease is registered in Poland, from a mean efficiency score of 91.35 percent to 79.78 percent ($\bar{\lambda}$ increases from 0.09 to 0.23) and in Turkey from 83.24 percent to 80.17 percent ($\bar{\lambda}$ increases from 0.19 to 0.22). The results are not surprising since these countries are either former communist countries, plagued by corruption and high costs due to over staffing that struggled through the 90's to transition to a market economy, or, in the case of Turkey, went through a financial crisis in the early 2000's.

Table 6.12: Efficiency Score - Posterior Means and Standard Deviation, 90% H.D.R.*

Country name	Obs.	No. banks	$r_j^\dagger$ $M_1^\Diamond$	$r_j^\dagger$ M_2°	Post. S.D. M_2°	H.D.R. M_2°
CROATIA	121	26	0.8979	0.5700	0.0351	[0.5114 , 0.6269]
DENMARK	375	78	0.8276	0.9686	0.0100	[0.9503 , 0.9825]
FRANCE	527	171	0.6655	0.9613	0.0127	[0.9380 , 0.9793]
GERMANY	8668	1471	0.8521	0.8395	0.0032	[0.8343 , 0.8448]
ITALY	1818	561	0.8051	0.9920	0.0014	[0.9894 , 0.9940]
NETHERLANDS	134	36	0.8263	0.9507	0.0208	[0.9112 , 0.9771]
POLAND	93	28	0.9135	0.7978	0.0501	[0.7162 , 0.8823]
ROMANIA	104	23	0.8550	0.3917	0.0442	[0.3195 , 0.4649]
SERBIA	80	25	0.6028	0.2459	0.0461	[0.1729 , 0.3247]
SLOVENIA	84	17	0.9193	0.9566	0.0162	[0.9261 , 0.9784]
SWEDEN	344	61	0.8696	0.9718	0.0085	[0.9562 , 0.9838]
SWITZERLAND	1188	221	0.6000	0.9849	0.0035	[0.9786 , 0.9900]
TURKEY	84	18	0.8324	0.8017	0.0368	[0.7434 , 0.8620]
UNITED KINGDOM	350	85	0.8519	0.9512	0.0184	[0.9163 , 0.9757]

Notes:
∗ Highest Density Region
† Efficiency score for country j
◊ The results were obtained in the previous chapter using individual fro ntiers for each country (model M_1).
∘ The results were obtained using a multiple lambda model (common frontier, allowing for the inefficiencies to differ for each country - model M_2).
Posterior moments are computed based on 50,000 points generated from the Gibbs sampling algorithm. The end points of the 90% confidence region are the 5^{th} and the 95^{th} percentiles of the posterior marginal densities.

The only country for which results do not vary much is Germany (the efficiency score decreases a little from 85.21 percent under the national frontier assumption to 83.95 percent under the common frontier assumption as $\bar{\lambda}$ increases from 0.16 to 0.17). The most dramatic changes are registered by Croatia, Romania, Serbia (for which the mean efficiency score plummets), France and Switzerland (for which there is a significant increase in the mean efficiency score).

All the other countries (Denmark, France, Italy, Netherlands, Slovenia, Sweden, Switzerland and UK) exhibit an increase of the mean efficiency score (as the posterior mean for λ decreases) relative to the common frontier in comparison to the individual frontier.

Table 6.13: σ^2 - Posterior Means and Standard Deviation , 90% H.D.R.*

Country name	Obs.	No. banks	σ^2 $M_1^{\lozenge}$	σ^2 M_2°	Post. S.D. M_2°	H.D.R. M_2°
CROATIA	121	26	0.0832	0.0567	0.0242	[0.0242 , 0.1015]
DENMARK	375	78	0.0939	0.2046	0.0152	[0.1810 , 0.2308]
FRANCE	527	171	0.0586	0.3014	0.0190	[0.2715 , 0.3339]
GERMANY	8668	1471	0.0329	0.0360	0.0009	[0.0345 , 0.0374]
ITALY	1818	561	0.0386	0.2612	0.0095	[0.2460 , 0.2771]
NETHERLANDS	134	36	0.3548	0.6351	0.0798	[0.5156 , 0.7753]
POLAND	93	28	0.1796	0.2721	0.0506	[0.1989 , 0.3628]
ROMANIA	104	23	0.1144	0.1258	0.0674	[0.0370 , 0.2526]
SERBIA	80	25	0.0988	0.3228	0.1757	[0.0849 , 0.6475]
SLOVENIA	84	17	0.0808	0.1264	0.0204	[0.0968 , 0.1632]
SWEDEN	344	61	0.0602	0.1458	0.0114	[0.1281 , 0.1655]
SWITZERLAND	1188	221	0.0470	0.3866	0.0175	[0.3586 , 0.4163]
TURKEY	84	18	0.0564	0.1085	0.0319	[0.0655 , 0.1674]
UNITED KINGDOM	350	85	0.4026	0.5486	0.0423	[0.4829 , 0.6211]

Notes:
∗ Highest Density Region
◊ The results were obtained in the previous chapter using individual frontiers for each country (model M_1).
○ The results were obtained using a multiple lambda model (common frontier , allowing for the inefficiencies to differ for each country - model M_2).
Posterior moments are computed based on 50,000 points generated from the Gibbs sampling algorithm.
The end points of the 90% confidence region are the 5^{th} and the 95^{th} percentiles of the posterior marginal densities.

The biggest increases in efficiency can be observed in the case of Switzerland (60 percent to 98.49 percent) and France ($\bar{r}$ increases from 66.55 percent to 96.13 percent). This is a result more in par with what we have expected especially from the Swiss banks. In general we observe an increase in the posterior mean of the σ^2 parameter (Table 6.13) as we switch from the national frontier to the common frontier, big changes being registered by Switzerland (from 0.047 to 0.3866), Netherlands (from 0.3548 to 0.6351), Italy (from 0.0386 to 0.2612), France (from 0.0586 to 0.3014) and Serbia (from 0.0988 to 0.3228) suggesting that the banks from these countries may deviate from the assumed “European” common frontier.

Another way to compare the countries in terms of bank efficiency is to perform pairwise comparisons by looking at the relative group inefficiencies, calculated as a ratio of the λ parameters of the two countries of interest.

Table 6.14 reports a matrix of these pairwise comparisons for all the 14 countries containing the posterior means of the λ_i/λ_j ratios, where i and j are country indexes. The highest ratios are registered (as expected) by Romania (120.37 times more inefficient than the Italian banks) and Serbia (181.4 times more inefficient than the Italian banks). Croatian banks are 71.99 times more inefficient than the Italian banks. For Germany (22.32), Poland (29.04) and Turkey (28.35), the relative group inefficiencies are also relatively high compared to the Italian banks. Much smaller ratios relative to the Italian banks are obtained for Denmark (4.09), France (5.06), Netherlands (6.47), Slovenia (5.67), Sweden (3.66), Switzerland (1.94) and UK (6.41).

In Table 6.15 we present the matrix results of the pairwise comparisons in terms of probability computations that the inefficiency in country i is less or equal than inefficiency in country j, ($\Pr[\lambda_i/\lambda_j \leq 1]$). As expected, the results confirm that Romania and Serbia have the least efficient banking sector, while the Italian and Swiss banks have the most cost efficient banks. For most countries, the pairwise comparisons from Table 6.15 indicate with high probability (sometimes > 0.99) which has the more efficient banks (Croatia in comparison to Romania or Serbia, Switzerland in comparison to all countries with the exception of Italy, etc.). Less decisive results are obtained for just a few of the pairwise comparisons. For example, the probability of the Swedish banks being more efficient than the Danish banks is just 0.60, while the probability of the British banks being more efficient than the Dutch banks is equal to 0.50. Slovenia and France, Slovenia and Netherlands, Denmark and France are the pairs for which the probabilities of one banking system being more efficient than the other suggest that they are very similar in terms of cost efficiency.

Table 6.14: Relative Group Type Inefficiency - $\lambda_i/\lambda_j{}^*$, Posterior Means

$\lambda_i/\lambda_j{}^*$	HR	DK	FR	DE	IT	NL	PL	RO	RS	SI	SE	CH	TR	UK
HR	1.00	19.57	15.96	3.23	71.99	13.28	2.71	0.61	0.40	14.65	21.63	39.07	2.67	13.02
DK	0.06	1.00	0.90	0.18	4.09	0.75	0.15	0.03	0.02	0.83	1.22	2.20	0.15	0.74
FR	0.07	1.37	1.00	0.23	5.06	0.93	0.19	0.04	0.03	1.03	1.51	2.76	0.19	0.91
DE	0.31	6.07	4.95	1.00	22.32	4.12	0.84	0.19	0.13	4.55	6.71	12.12	0.83	4.04
IT	0.01	0.28	0.23	0.05	1.00	0.19	0.04	0.01	0.01	0.21	0.31	0.56	0.04	0.19
NL	0.09	1.77	1.43	0.29	6.47	1.00	0.25	0.06	0.04	1.31	1.95	3.51	0.24	1.17
PL	0.41	7.90	6.44	1.30	29.04	5.35	1.00	0.24	0.16	5.89	8.73	15.73	1.06	5.26
RO	1.69	32.74	26.67	5.40	120.37	22.23	4.53	1.00	0.68	24.50	36.20	65.39	4.46	21.78
RS	2.50	49.30	40.20	8.10	181.40	33.50	6.80	1.50	1.00	36.90	54.50	98.50	6.70	32.80
SI	0.08	1.54	1.26	0.25	5.67	1.04	0.21	0.05	0.03	1.00	1.71	3.07	0.21	1.03
SE	0.05	0.99	0.81	0.16	3.66	0.67	0.14	0.03	0.02	0.75	1.00	1.99	0.14	0.66
CH	0.06	0.53	0.43	0.09	1.94	0.36	0.07	0.02	0.01	0.40	0.59	1.00	0.07	0.35
TR	0.40	7.70	6.27	1.27	28.35	5.22	1.05	0.24	0.16	5.75	8.51	15.37	1.00	5.11
UK	0.09	1.74	1.41	0.29	6.41	1.19	0.24	0.05	0.04	1.30	1.93	3.46	0.24	1.00

Notes:
$*$ where i=row number , j=column number Posterior moments are computed based on 50,000 points generated from the Gibbs sampling algorithm.

Table 6.15: Efficiency Comparisons Across Countries - $P[\lambda_i/\lambda_j \leq 1]^*$

$P[\lambda_i/\lambda_j \leq 1]^*$	HR	DK	FR	DE	IT	NL	PL	RO	RS	SI	SE	CH	TR	UK
HR	> 0.99	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	> 0.99	> 0.99	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01
DK	> 0.99	> 0.99	0.68	> 0.99	< 0.01	0.78	> 0.99	> 0.99	> 0.99	0.74	0.40	0.03	> 0.99	0.81
FR	> 0.99	0.32	> 0.99	> 0.99	< 0.01	0.66	> 0.99	> 0.99	> 0.99	0.57	0.24	0.02	> 0.99	0.66
DE	> 0.99	< 0.01	< 0.01	> 0.99	< 0.01	< 0.01	0.80	> 0.99	> 0.99	< 0.01	< 0.01	< 0.01	0.86	< 0.01
IT	> 0.99	> 0.99	> 0.99	> 0.99	> 0.99	> 0.99	> 0.99	> 0.99	> 0.99	> 0.99	> 0.99	0.98	> 0.99	> 0.99
NL	> 0.99	0.22	0.34	> 0.99	< 0.01	> 0.99	> 0.99	> 0.99	> 0.99	0.42	0.16	0.01	> 0.99	0.50
PL	> 0.99	< 0.01	< 0.01	0.20	< 0.01	< 0.01	> 0.99	> 0.99	> 0.99	< 0.01	< 0.01	< 0.01	0.47	< 0.01
RO	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	> 0.99	0.99	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01
RS	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	0.01	> 0.99	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01
SI	> 0.99	0.26	0.43	> 0.99	< 0.01	0.58	> 0.99	> 0.99	> 0.99	> 0.99	0.20	0.01	> 0.99	0.59
SE	> 0.99	0.60	0.76	> 0.99	< 0.01	0.84	> 0.99	> 0.99	> 0.99	0.80	> 0.99	0.06	> 0.99	0.86
CH	> 0.99	0.97	0.98	> 0.99	0.02	0.99	> 0.99	> 0.99	> 0.99	0.99	0.94	> 0.99	> 0.99	0.99
TR	> 0.99	< 0.01	< 0.01	0.14	< 0.01	< 0.01	0.53	> 0.99	> 0.99	< 0.01	< 0.01	< 0.01	> 0.99	< 0.01
UK	> 0.99	0.19	0.34	> 0.99	< 0.01	0.50	> 0.99	> 0.99	> 0.99	0.41	0.14	0.01	> 0.99	> 0.99

Notes:
$*$ where i=row number , j=column number
The probabilities are computed based on 50,000 points generated from the Gibbs sampling algorithm.

6.4 Posterior Marginal Densities for λ, Efficiency Score, and σ^2

As in the previous chapter, we follow up with a visual presentation of the results for the common frontier by including the graphs (Figure 6.21 through Figure 6.34) of the smoothed posterior marginal densities for λ, σ^2, and efficiency score.

The densities for λ or the efficiency score exhibit asymmetries if the posterior mean for λ is close to zero, and evidently if the posterior mean for the efficiency score gets close to one (as observed for Denmark, France, Italy, Netherlands, Slovenia, Sweden and Switzerland). For the countries with high inefficiencies or a large number of observations, the densities for λ and the efficiency score look more symmetric, almost normal (as in the case of Croatia, Germany, Poland, Romania, Serbia or Turkey).

The posterior marginal densities for σ^2 show asymmetries in the case of the countries with less observations like Poland, Turkey, Serbia, Romania, Croatia, Netherlands, Slovenia and look more symmetric for the countries with more observations like Germany, France, or Italy.

Compared to the posterior marginal distributions for λ, σ^2, and efficiency score drawn based on the national frontiers (chapter 5), we observe that these plots are smoother. This happens because even though the λ's and the σ^2's are estimated based on each country's number of observations, the β's are common to all countries and therefore estimated based on the total number of observations ($N = 13,970$). Looking at the full conditional distributions for λ, σ^2 and v, this is expected to have an impact on the shape, width and location of their posterior marginal distributions.

Croatia

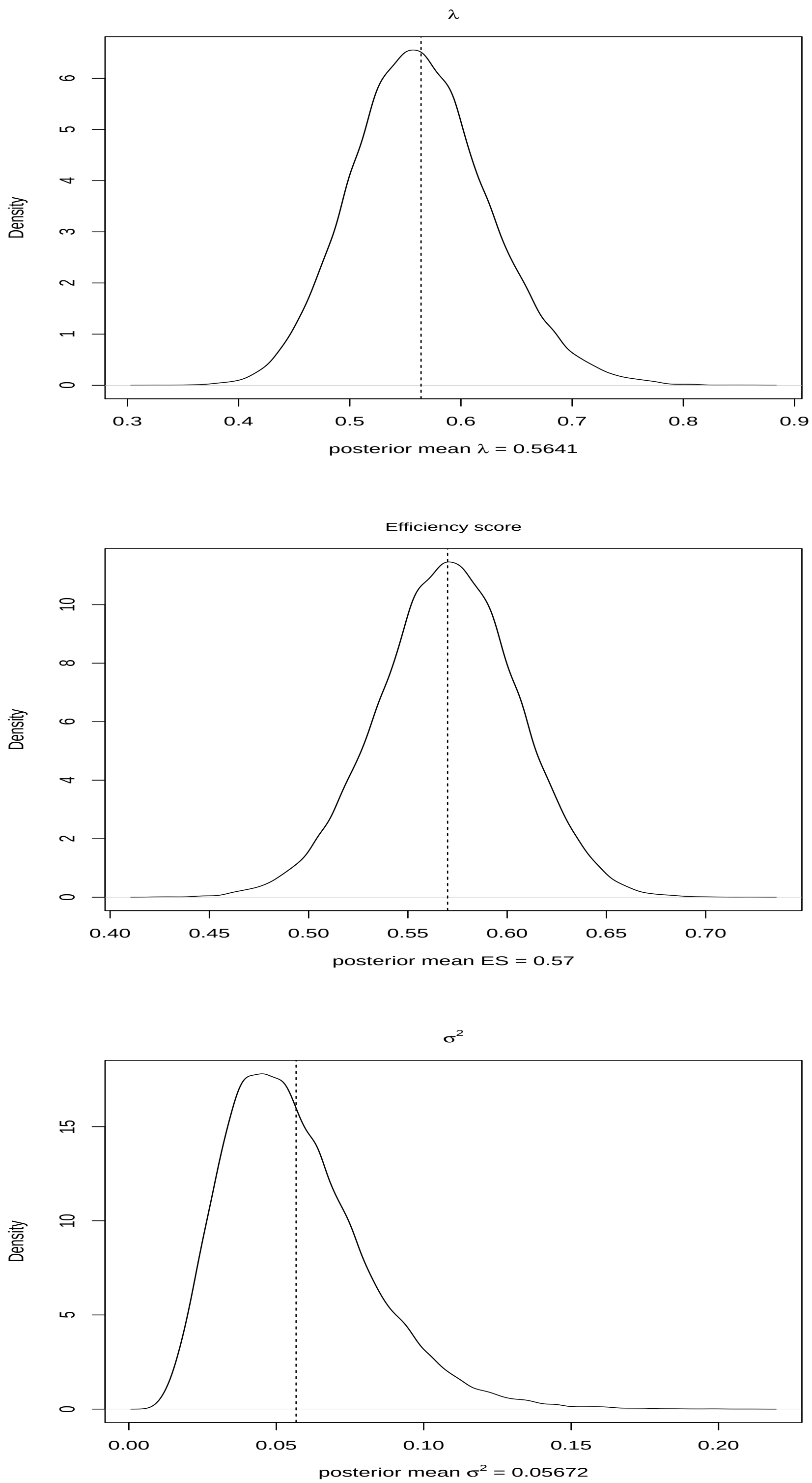


Figure 6.21: Posterior Marginal Densities for λ, Efficiency Score and σ^2.

Denmark

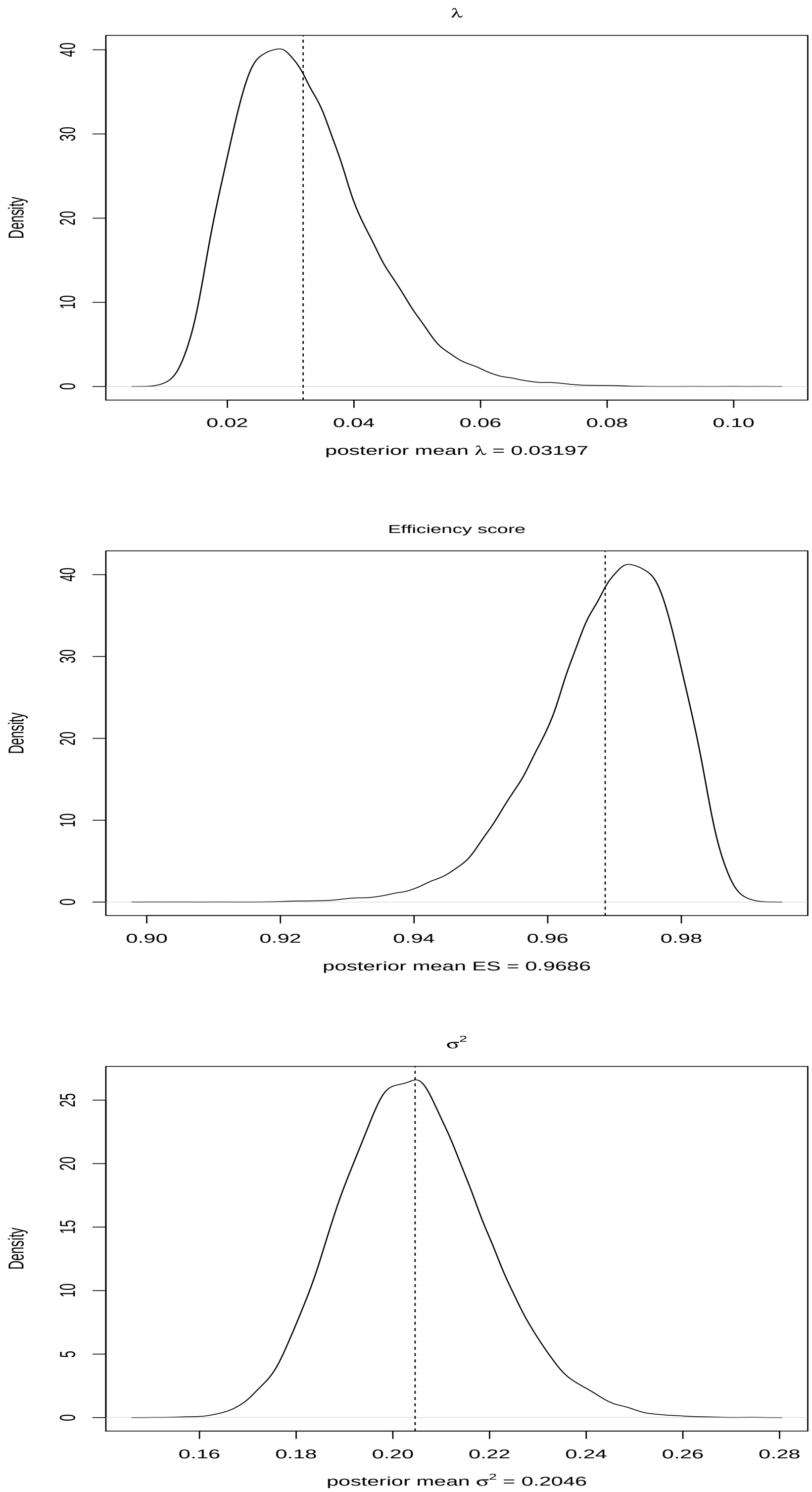


Figure 6.22: Posterior Marginal Densities for λ, Efficiency Score and σ^2.

France

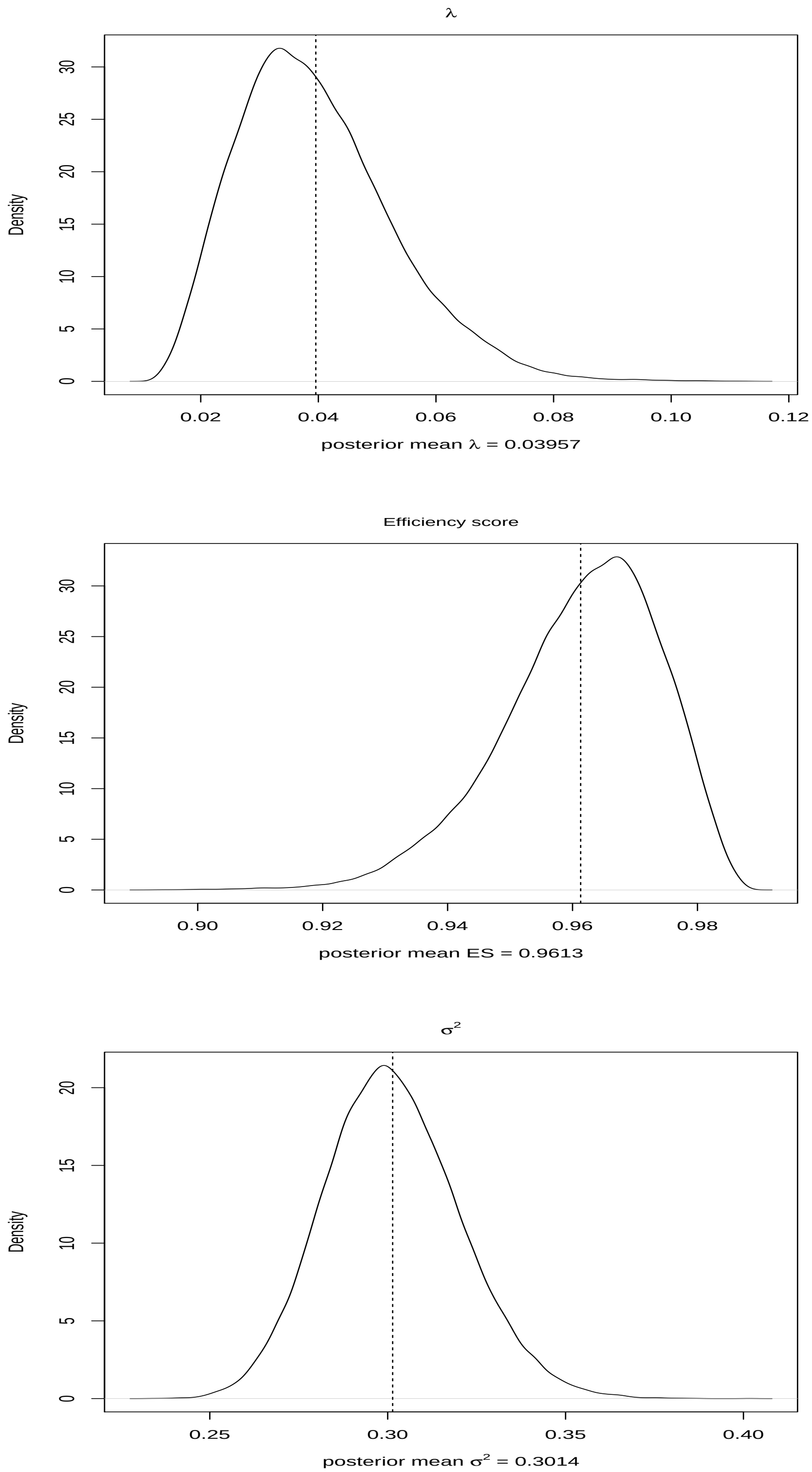


Figure 6.23: Posterior Marginal Densities for λ, Efficiency Score and σ^2.

Germany

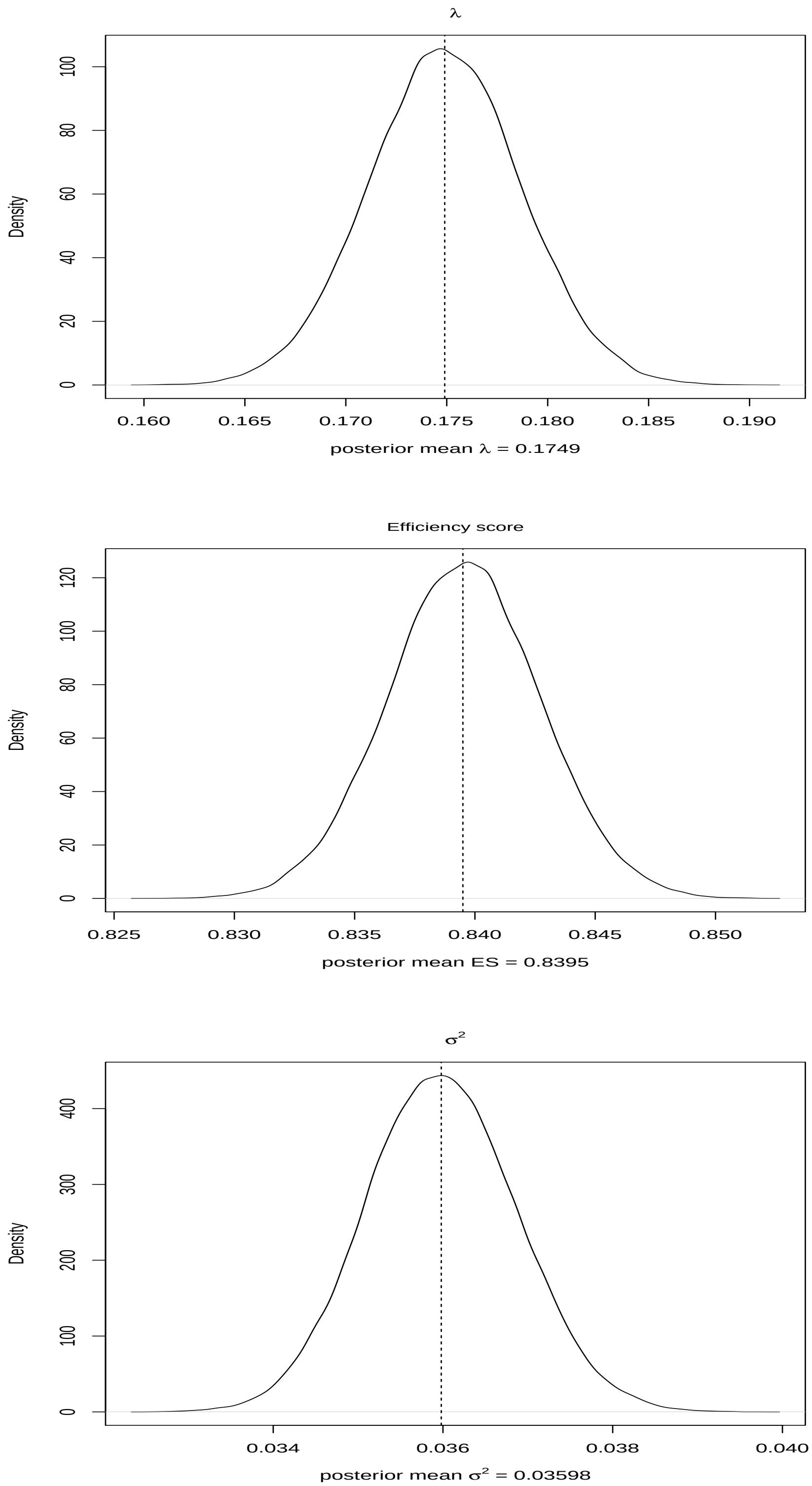


Figure 6.24: Posterior Marginal Densities for λ, Efficiency Score and σ^2.

Italy

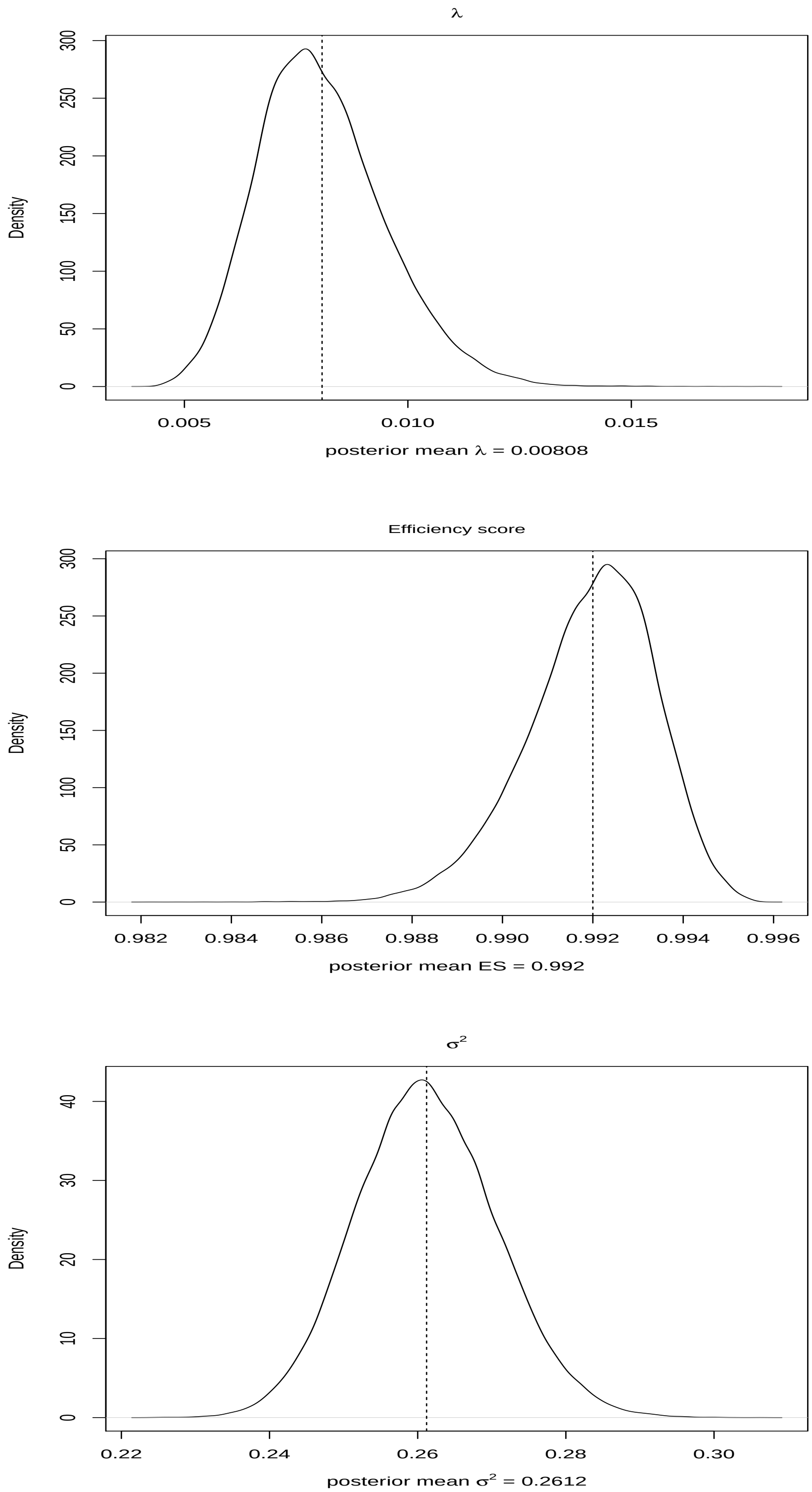


Figure 6.25: Posterior Marginal Densities for λ, Efficiency Score and σ^2.

Netherlands

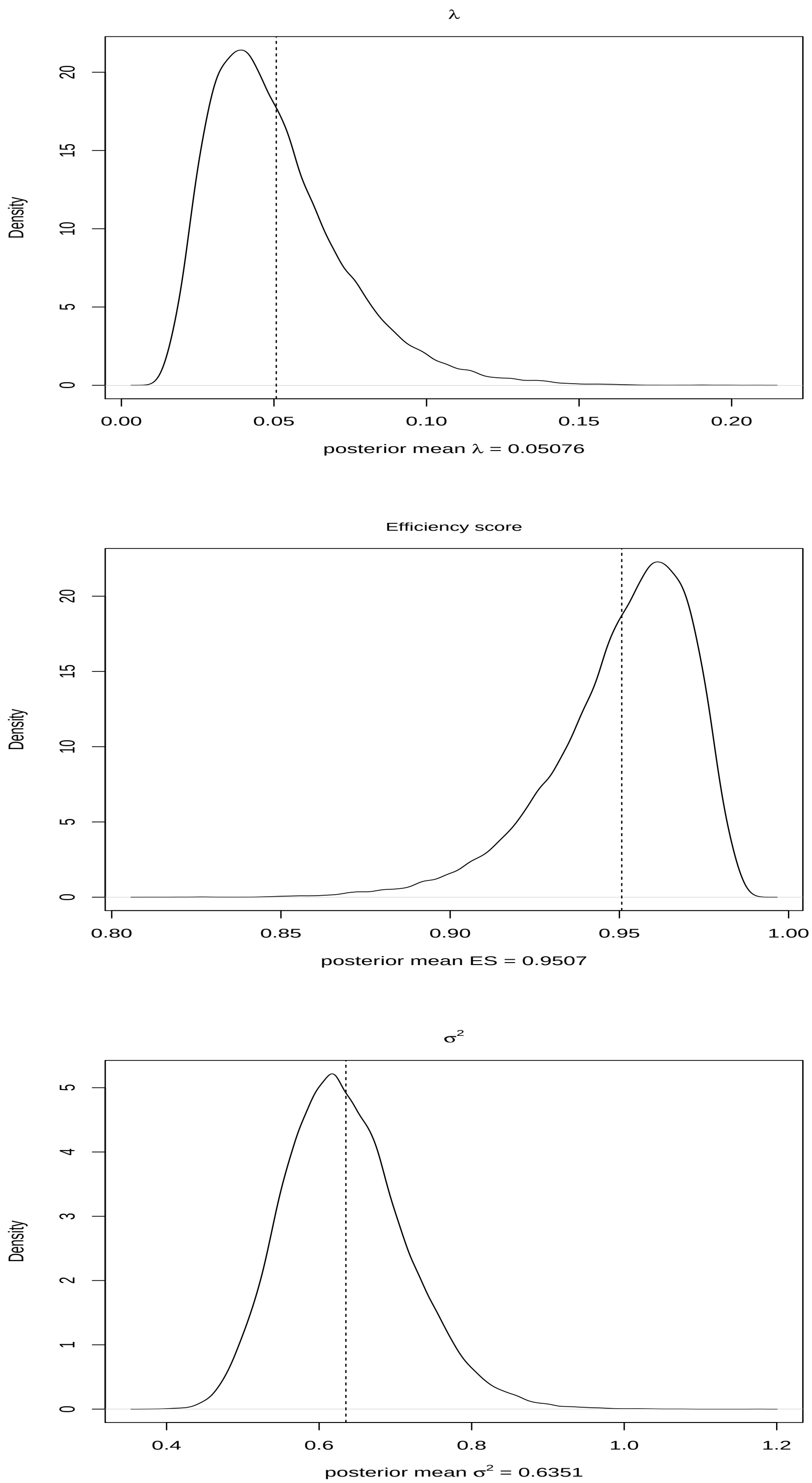


Figure 6.26: Posterior Marginal Densities for λ, Efficiency Score and σ^2.

Poland

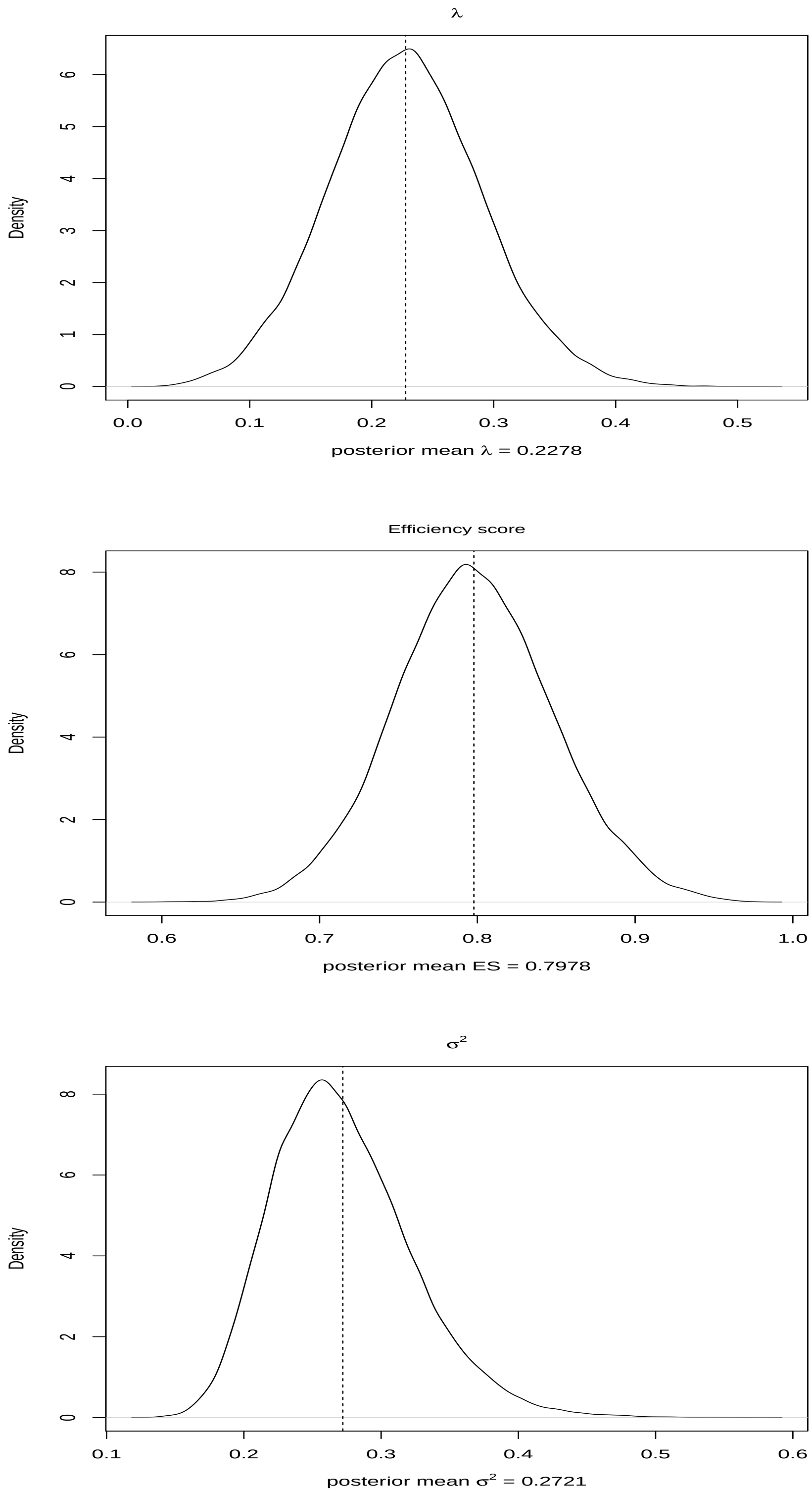


Figure 6.27: Posterior Marginal Densities for λ, Efficiency Score and σ^2.

Romania

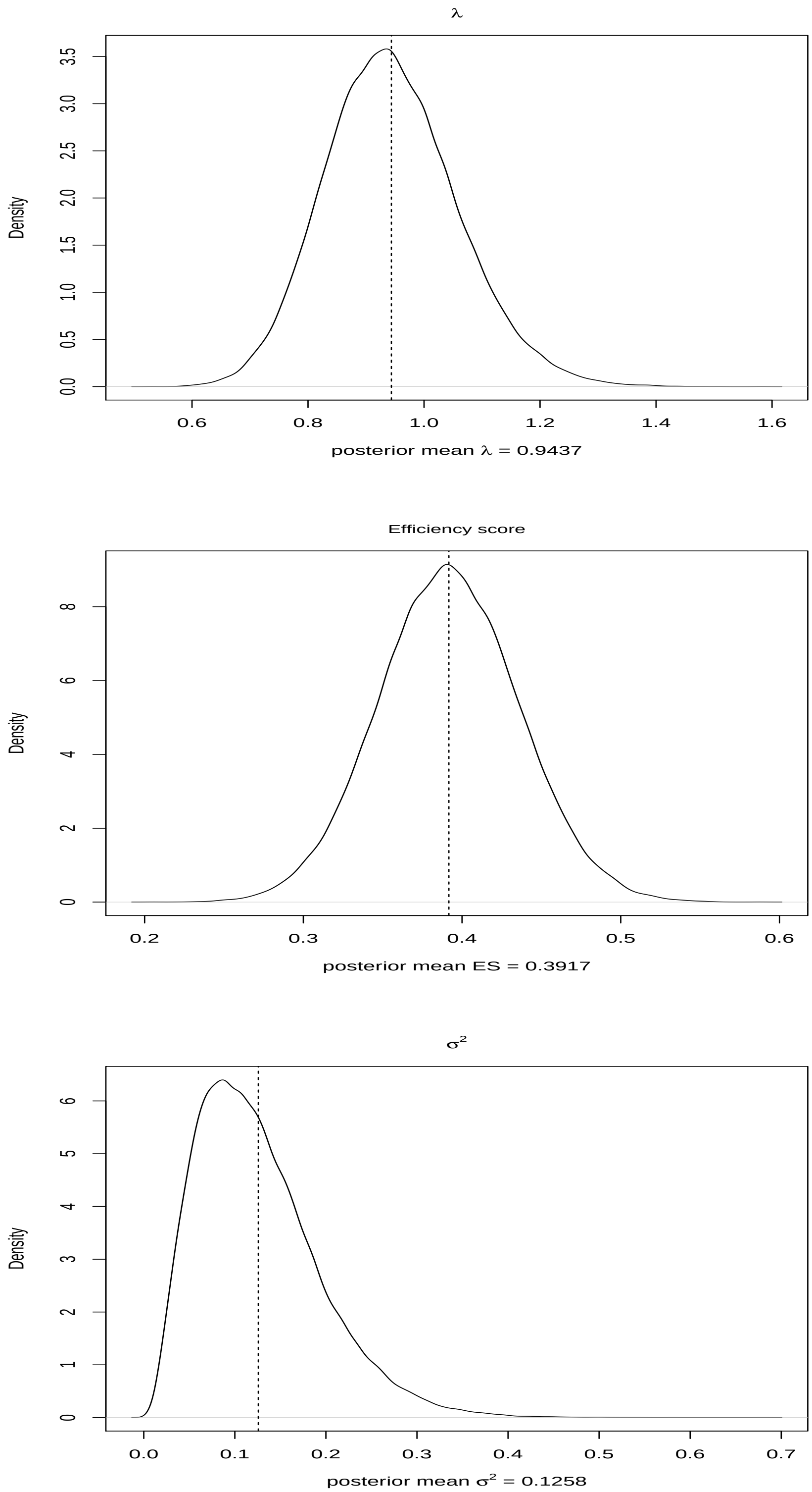


Figure 6.28: Posterior Marginal Densities for λ, Efficiency Score and σ^2.

Serbia

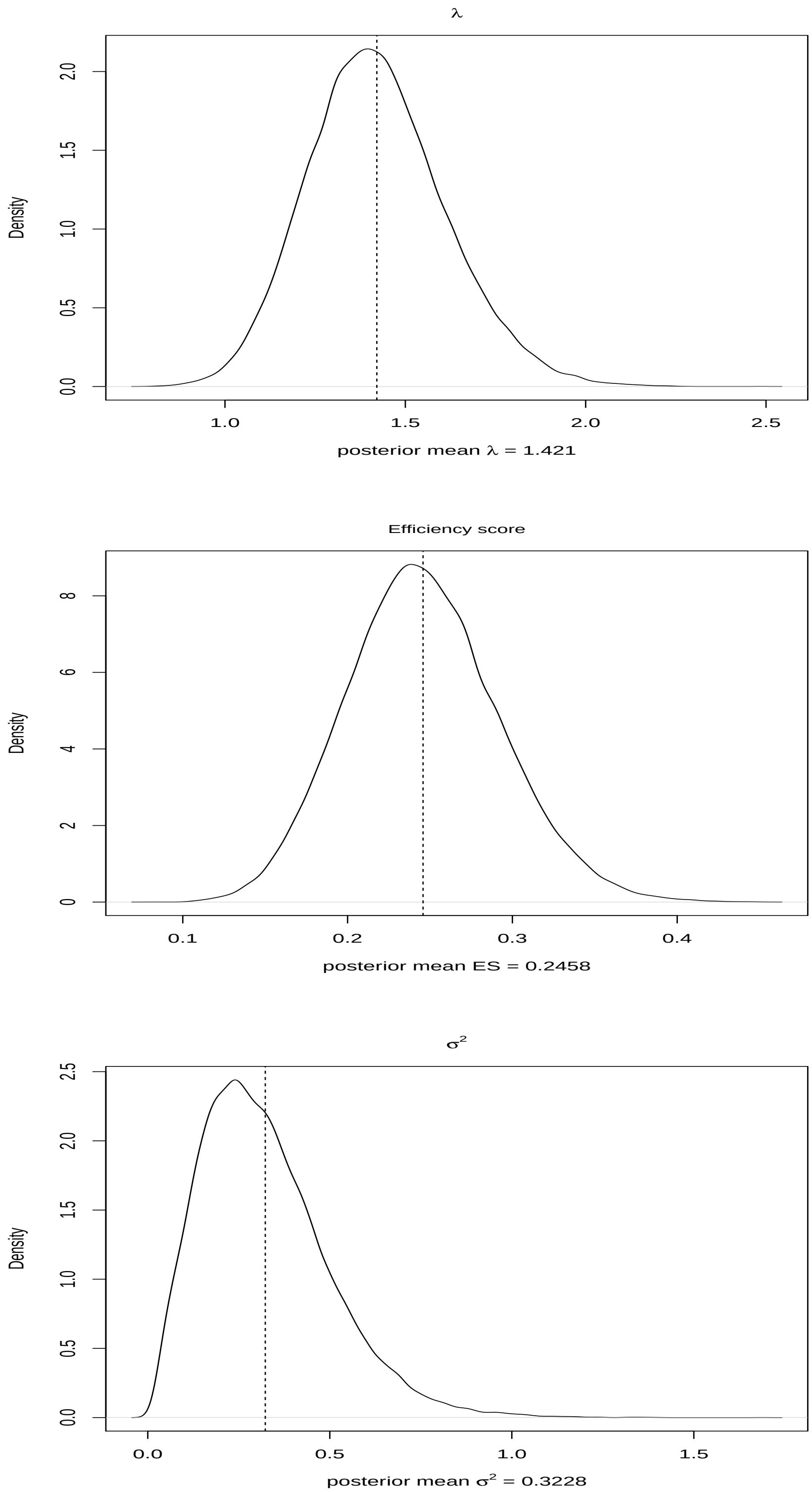


Figure 6.29: Posterior Marginal Densities for λ, Efficiency Score and σ^2.

Slovenia

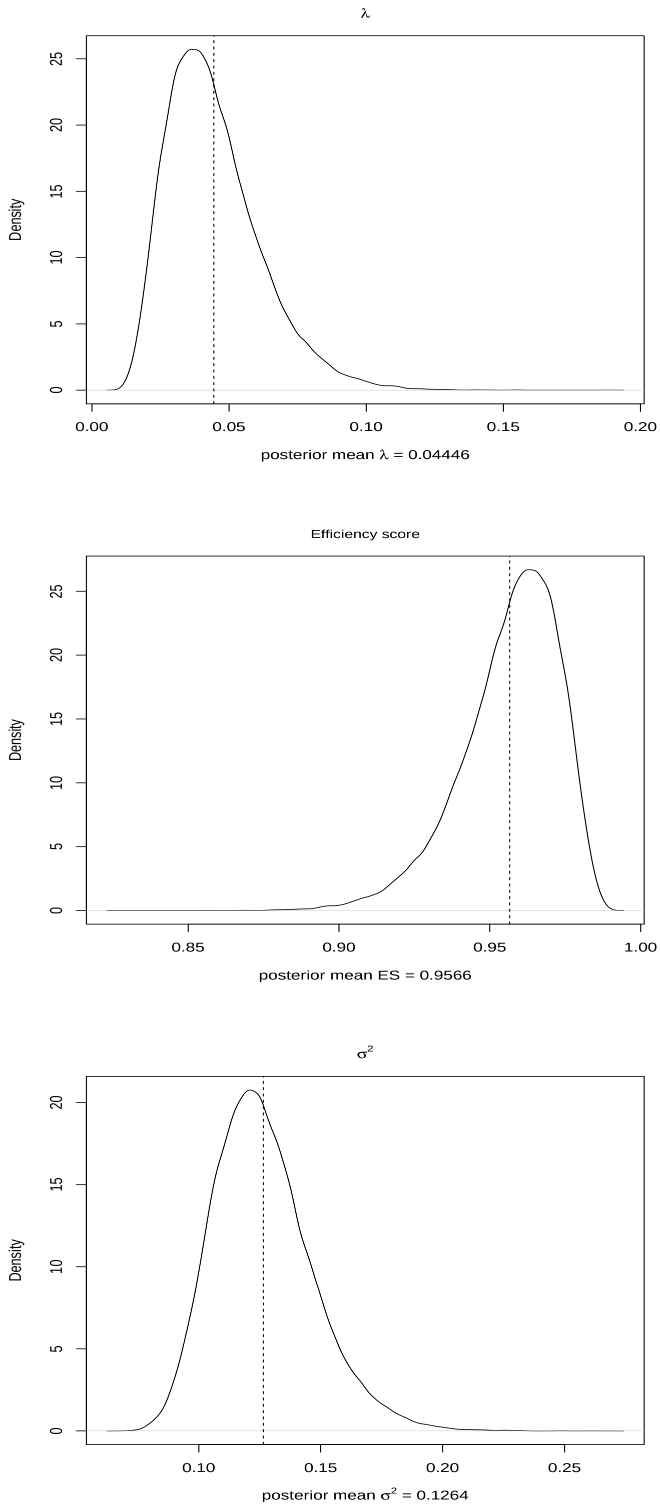


Figure 6.30: Posterior Marginal Densities for λ, Efficiency Score and σ^2.

Sweden

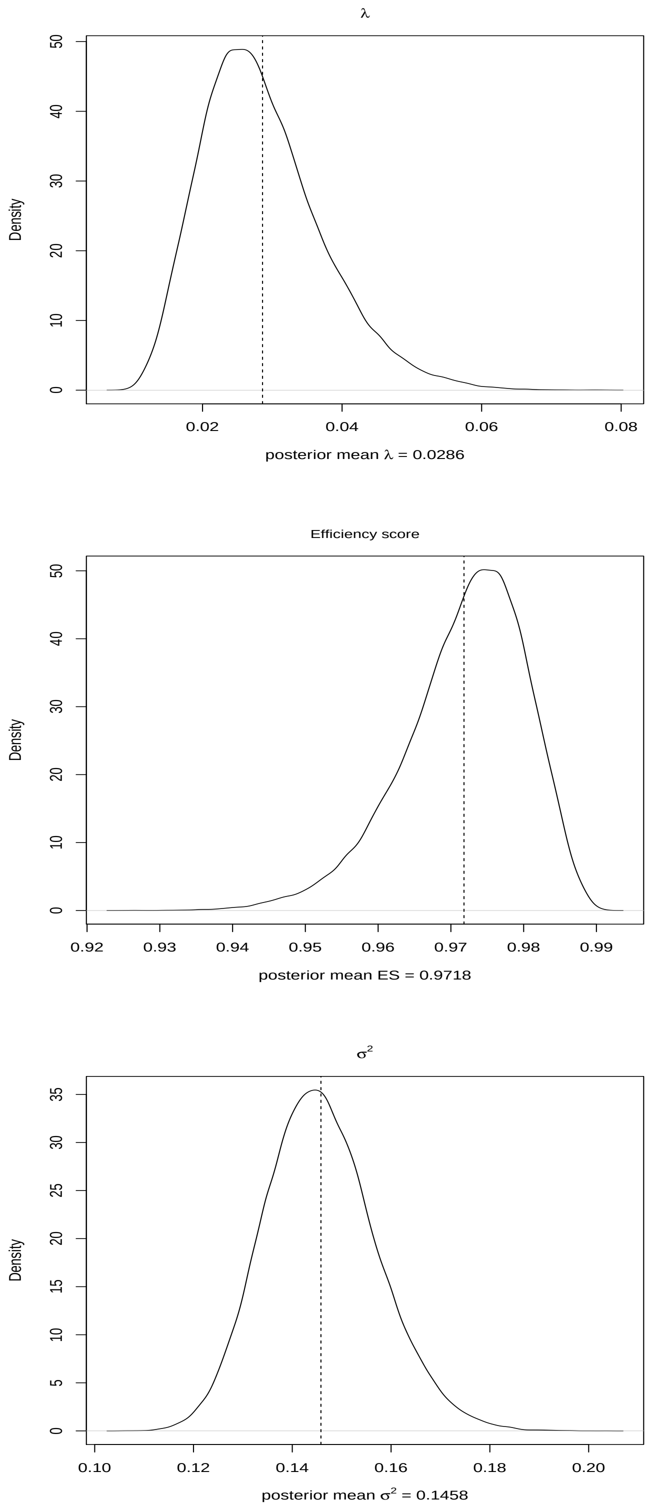


Figure 6.31: Posterior Marginal Densities for λ, Efficiency Score and σ^2.

Switzerland

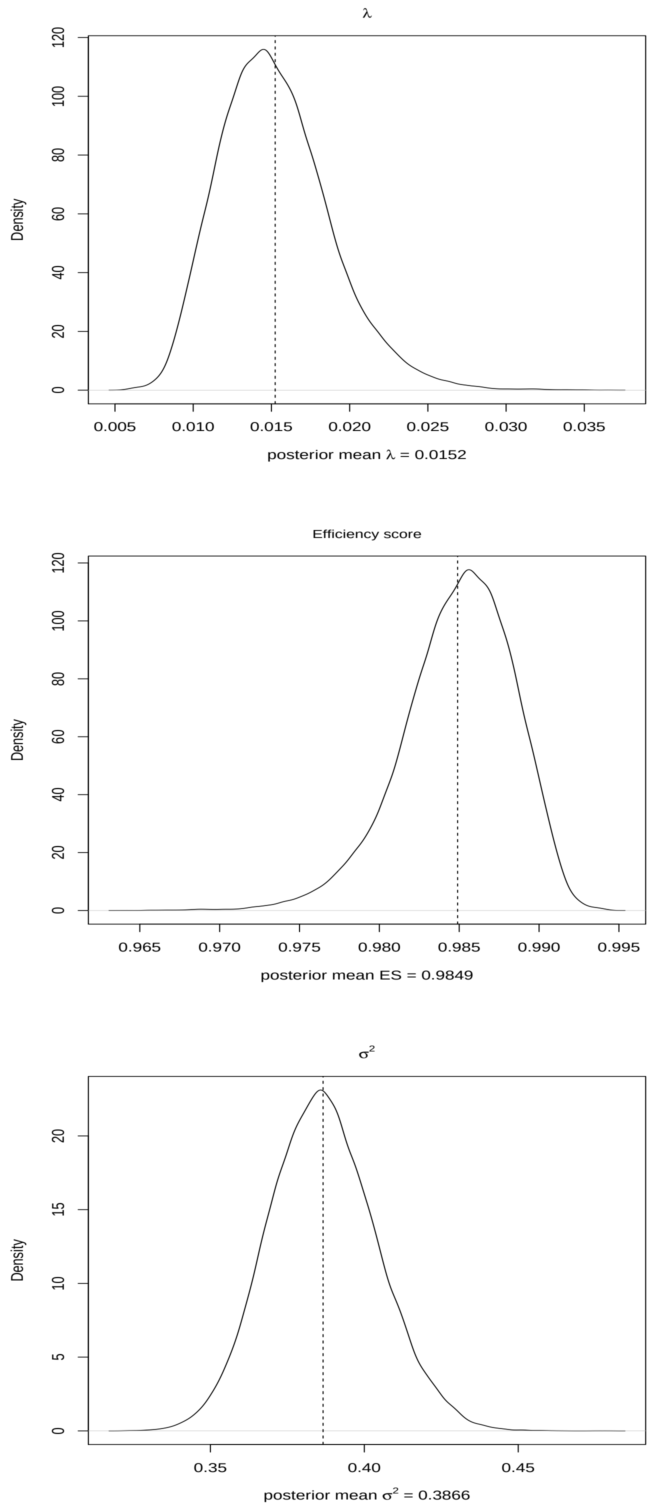
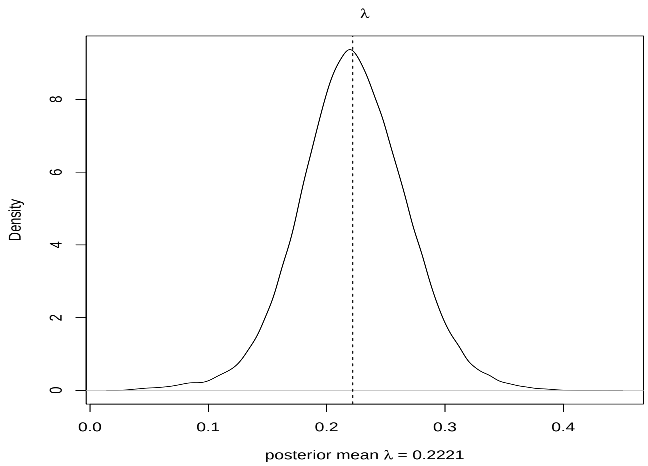
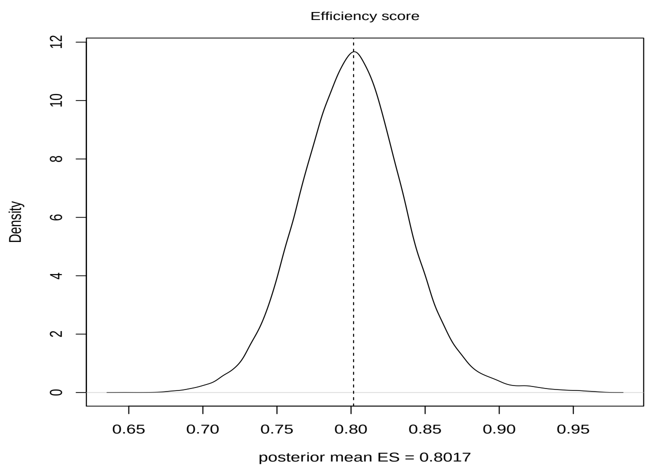


Figure 6.32: Posterior Marginal Densities for λ, Efficiency Score and σ^2.

Turkey





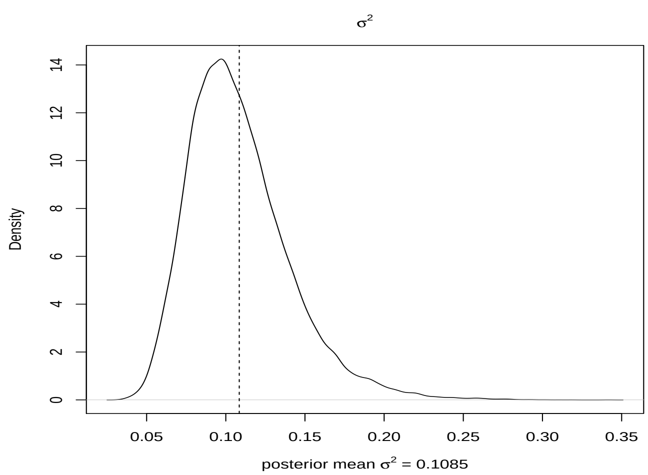


Figure 6.33: Posterior Marginal Densities for λ, Efficiency Score and σ^2.

United Kingdom

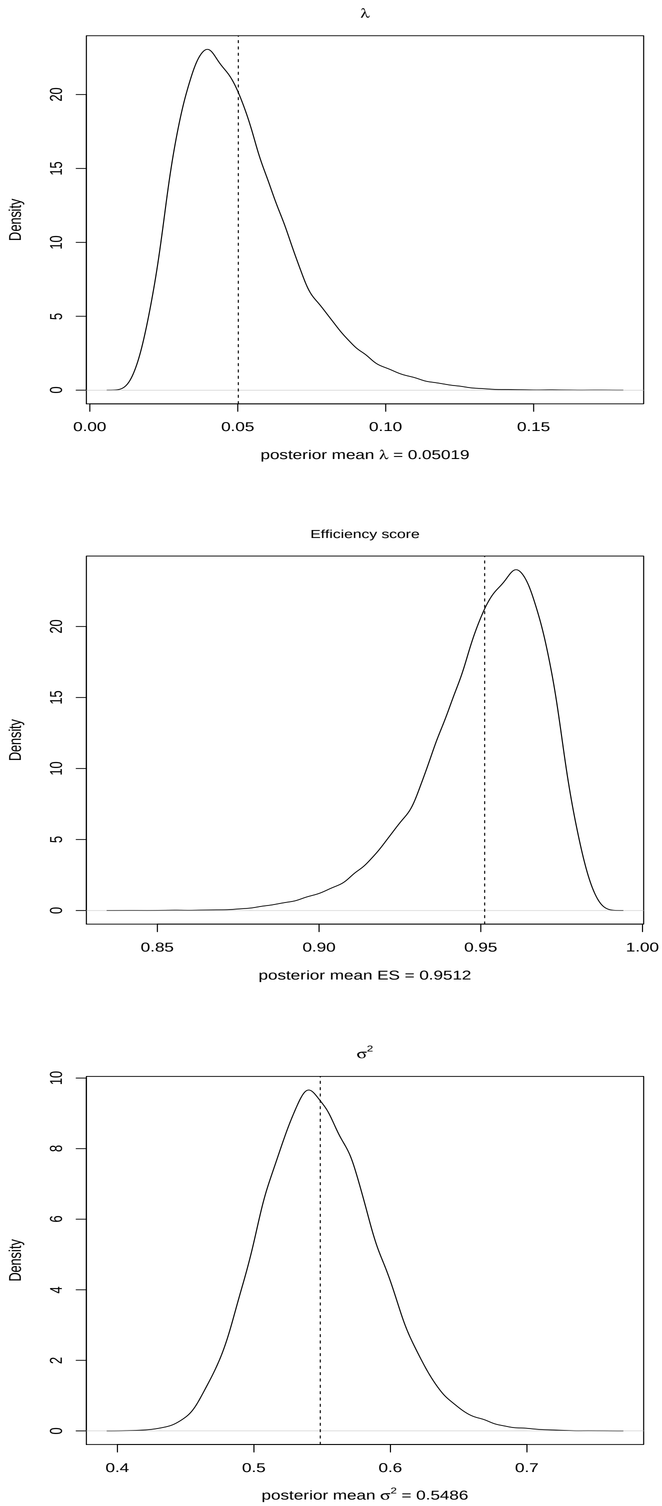


Figure 6.34: Posterior Marginal Densities for λ, Efficiency Score and σ^2.

6.5 Conclusions

In this chapter we measure country specific efficiencies against a common frontier to address the cross-country comparison problems raised by the previous individual country frontier approach.

As pointed out by Berger (2007), even if this approach solves the problem of comparing efficiencies that were estimated relative to different benchmark frontiers, it's not without downfalls. By assuming a common frontier, the impact that the different economic environments might have on the banks' cost structure (due to regulations, culture etc.) is ignored or difficult to control for. Previous research found that the assumption of a common technology "induces a strong bias in cross country comparisons and may yield misleading results"[7]. We find significant changes in efficiency levels when determined against the common frontier as opposed to single frontier for most countries, with the exception of Germany, Slovenia and Turkey.

We find that, by allowing for heterogeneity within the model (common frontier), the results for the technology parameters differ from the case in which homogeneity is assumed (the pooled model from chapter 5). Economies of scale computations for the same selected banks as in chapter 5 confirm this idea. While the posterior means of the economies of scale remain consistently greater than one for most banks, irrespective of bank sizes, they are significantly different for the two models (M1 and M2). Still, we can conclude that the majority of banks we selected could reduce costs by increasing output.

As the efficiency is determined with respect to a common frontier, we can now compare the relative efficiency levels and we find that the most efficient banks are from Italy (99.2 percent), Switzerland (98.49 percent), Sweden (97.18 percent), Denmark (96.86 percent),

[7] Bos and Schmiedel (2007), Dietsch and Lozano-Vivas (2000), Bikker (2002).

France (96.13 percent), Slovenia (95.66 percent), and UK (95.12 percent). The least efficient banks are from Serbia (24.59 percent), Romania (39.17 percent) and Croatia (57 percent). The results are not surprising when it comes to Romania, Serbia, Croatia or Switzerland but the Italian, British and French banks have unexpectedly low costs.

The results for σ^2 raise doubts about the validity of the common cost frontier assumption which in turn raises the question of how best to tackle the task of international comparisons of the banking systems. If the individual frontiers do not allow for comparisons of efficiencies across countries and the common frontier approach risks forcing countries to share technology against evidence to the contrary, is there a "middle ground"?

Next chapter introduces a model that nests both of these approaches and through the use of an informative prior varied according our beliefs about the frontiers, the existence of different "sub-frontiers" is permitted.

Chapter 7
A More General Multi-Country Bayesian Stochastic Cost Frontier

7.1 Introduction

The previous two chapters implemented Bayesian stochastic cost frontier models that illustrate two approaches in the banking literature as summarized by Berger (2007) for comparing efficiency across countries. In chapter 5, model M1, we identified 14 individual country frontiers based on each country's banks, investigating their efficiency relative to these own-nation frontiers. Since we have 14 "reference frontiers" when determining the efficiency levels, conclusions about relative efficiencies between countries are difficult to draw. In chapter 6, model M2, a common frontier is drawn for all the countries by pooling together the data and determining each country's relative efficiency as a deviation from this shared, single frontier. Comparisons across countries are now possible since the "reference frontier" is the same. However, the common frontier implicitly assumes a similar regulation environment and technology in all countries.

The present chapter introduces a Bayesian stochastic translog cost frontier with country dummy variables and an informative prior that allows for a continuous shift from individual country frontiers (M1) to a common frontier (M2). By varying the degree of precision on the prior distribution of the frontier parameters (the β's), the model nests both previous approaches. This methodology also permits us to investigate if indeed there are different frontiers or if the countries share the same technology.

7.2 Model Specifications and Methodology

As before, this is another composite error model that constructs an efficient frontier from which the individual firm deviates due to both inefficiency (incurring higher costs, v_{ij}) and measurement error or luck (the random aspect, u_{ij}). The introduction of the dummy variables are an allowance for deviations from the common frontier and are the main change in this chapter. By using dummy variables, we can include all 14 frontiers in the model. As a result, the number of technology parameters (β's) increases from 10 to 140 as follows:

$$\begin{aligned} y_{ij} = & \sum_{k=1}^{10} \beta_{ik} x_{ik} + \sum_{k=11}^{20} \beta_{ik} x_{ik} \delta_{HR} + \sum_{k=21}^{30} \beta_{ik} x_{ik} \delta_{DK} + \sum_{k=31}^{40} \beta_{ik} x_{ik} \delta_{FR} \\ & + \sum_{k=41}^{50} \beta_{ik} x_{ik} \delta_{IT} + \sum_{k=51}^{60} \beta_{ik} x_{ik} \delta_{NL} + \sum_{k=61}^{70} \beta_{ik} x_{ik} \delta_{PL} + \sum_{k=71}^{80} \beta_{ik} x_{ik} \delta_{RO} + \\ & + \sum_{k=81}^{90} \beta_{ik} x_{ik} \delta_{RS} + \sum_{k=91}^{100} \beta_{ik} x_{ik} \delta_{SI} + \sum_{k=101}^{110} \beta_{ik} x_{ik} \delta_{SE} + \sum_{k=111}^{120} \beta_{ik} x_{ik} \delta_{CH} + \\ & + \sum_{k=121}^{130} \beta_{ik} x_{ik} \delta_{TR} + \sum_{k=131}^{140} \beta_{ik} x_{ik} \delta_{UK} + u_{ij} + v_{ij} \end{aligned}$$

where $i = 1, ..., N$ (bank i), j is the country index ($j = 1, .., 14$) and δ_{HR}, δ_{DK}, δ_{FR}, δ_{IT}, δ_{NL}, δ_{PL}, δ_{RO}, δ_{RS}, δ_{SI},δ_{SE}, δ_{CH}, δ_{TR}, δ_{UK} are dummy variables that take the value one if the bank i originates in the corresponding country and zero otherwise.

We used Germany as the reference country as it has the most observations, while the rest of the countries follow in alphabetical order as before.

This means that if we are interested in the frontier parameters for Germany, we focus on β_1 through β_{10} ($\beta_{1,DE} = \beta_1$, etc.). For all the other countries, the technology parameters are obtained by adding to the reference country's β, the value of the corresponding β parameter that was paired with the country's dummy as follows: $\beta_{1,HR} = \beta_1 + \beta_{11}$,..., $\beta_{10,HR} = \beta_{10} + \beta_{20}$, while $\beta_{1,UK} = \beta_1 + \beta_{131}$,..., $\beta_{10,UK} = \beta_{10} + \beta_{140}$.

We define the following matrices and vectors:

$$\text{Z} = \begin{pmatrix} X_{DE} & 0 & 0 & 0 & \cdots & 0 & 0 \\ X_{HR} & X_{HR} & 0 & 0 & \cdots & 0 & 0 \\ X_{DK} & 0 & X_{DK} & 0 & \cdots & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ X_{UK} & 0 & 0 & 0 & \cdots & 0 & X_{UK} \end{pmatrix}_{(N \times 140)}$$

where $X_{DE} = X_1$, $X_{HR} = X_2$, $X_{DK} = X_3$, ..., $X_{UK} = X_{14}$ are the independent variables matrices from all the countries, with $N = N_{DE} + N_{HR} + ... + N_{UK}$ the total number of observations obtained by adding up the number of observations from each country (i.e. $N_{DE} = N_1$ being the number of bank-year observations for Germany, $N_{HR} = N_2$ for Croatia, etc.). Let $K_j = \sum_{n=1}^{j} K_n$ and $K_0 = 0$. The rows from 1 to K_1 are the N_1 stacked observations for Germany (X_{DE}) and in general, the rows from $K_{j-1} + 1$ to K_j are the N_j stacked observations for country j, for $j = 1, ..., 14$.

$$\boldsymbol{\beta} = \begin{pmatrix} \beta_1 \\ \vdots \\ \beta_{11} \\ \vdots \\ \beta_{140} \end{pmatrix}, \quad \mathbf{y} = \begin{pmatrix} \mathbf{y}_{HR} \\ \mathbf{y}_{DK} \\ \mathbf{y}_{FR} \\ \vdots \\ \mathbf{y}_{UK} \end{pmatrix}, \quad \Sigma = \begin{pmatrix} \Sigma_{DE} & 0 & \cdots & & & 0 \\ 0 & \Sigma_{HR} & 0 & \cdots & & 0 \\ 0 & 0 & \Sigma_{DK} & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & \cdots & 0 & 0 & \Sigma_{UK} \end{pmatrix}$$

Where Σ is the data variance-covariance $N \times N$ diagonal matrix in which the variance corresponding to the n's observation is inserted on row n.

The covariance terms are equal to zero and above we wrote Σ in a meaningful fashion using block diagonal matrices of dimensions $N_j \times N_j$, $j = 1, ..., 14$ ($\Sigma_{DE} = \Sigma_{u_1} = \text{diag}[\sigma^2_{DE}] = \text{diag}[\sigma^2_{u_1}]$, $\Sigma_{HR} = \Sigma_{u_2} = \text{diag}[\sigma^2_{HR}] = \text{diag}[\sigma^2_{u_2}]$, etc.) to convey the idea that while each country has a different variance parameter, within the same country, the σ^2_u's are the same.

The statistical noises $u_{ij} \sim N(0, \sigma^2_{u_j})$ are still normally distributed, where i is the bank index and $j = 1, ..., 14$ is the country index, with $\mathbf{u} = (\mathbf{u}_{DE}, \mathbf{u}_{HR}, \mathbf{u}_{DK}, ..., \mathbf{u}_{UK})^T = (\mathbf{u}_1, \mathbf{u}_2, \mathbf{u}_3 ..., \mathbf{u}_{14})^T$.

The inefficiency terms, $v_{ij} \sim EXP(\lambda_j)$ follow exponential distributions, and we construct the $N \times 1$ inefficiency vector $\mathbf{v} = (\mathbf{v}_{DE}, \mathbf{v}_{HR}, \mathbf{v}_{DK}, ..., \mathbf{v}_{UK})^T = (\mathbf{v}_1, \mathbf{v}_2, \mathbf{v}_3, ..., \mathbf{v}_{14})^T$, while $\lambda_{DE} = \lambda_1$, $\lambda_{HR} = \lambda_2$, $\lambda_{DK} = \lambda_3$, etc.

Now, using the notations defined above, the model can be written in matrix form as:

$$\mathbf{y} = \mathbf{Z}\boldsymbol{\beta} + \mathbf{v} + \mathbf{u}$$

Note that this is not a classical matrix form notation of a dummy variables model as matrix Z was obtained by already including the dummy information so that the model can be re-written as a classical linear regression in order to simplify the formulas for the posterior marginal distributions and make the connection to the previous models.

Further we specify the choice of priors to complete the presentation of the statistical model and in doing so we follow Koop, Osiewalski and Steel (1994), but also Geweke (2005) and Gelman et al. (2004).

- we use an informative prior for $\boldsymbol{\beta} \sim N(\boldsymbol{\beta}_p, H_p^{-1})$, where $\boldsymbol{\beta}_p$ is a 140×1 vector of constants and H_p is a 140×140 positive definite matrix of constants. We specify $\boldsymbol{\beta}_p = (0, 0, ..., 0)^T$ as the null vector and construct the prior precision matrix as a diagonal matrix such that the prior variance on linear terms is equal to 10 and on the quadratic or interaction terms is equal to 1 (in essence, H_p^{-1} is a block diagonal matrix and on its diagonal we repeat 14 times the diagonal matrix with the elements $[10, 10, 1, 10, 1, 10, 1, 1, 1, 1])$ [1]. A new component of the prior is the scale factor, S which is a constant used to multiply rows 11 through 140 of the prior precision matrix. We will run the Gibbs sample for different values of the scale factor S: 0.1; 1; 1,000; 5,000; 10,000; 25,000; 50,000; 75,000; 100,000; 250,000; 500,000; 750,000; 1,000,000; 10,000,000 and 1,000,000,000. The higher the value for S, the stronger the prior. The high magnitude priors push the frontiers together (they shrink into one common frontier as in model M2), while the lower values ($S = 1$, $S = 0.1$) will generate individual country frontiers like the first model. As observed by Knight, Hill and Sirmans (1992), this is similar to the frequentist Stein rule estimators. In order to avoid confusion, we will keep the generic notation H_p for the prior precision matrix and mention separately the scale factor's value every time it changes.

- a gamma[2] prior[3] for each $\sigma_{u_j}^{-2}$, with $j = 1, ..., 14$: $\pi(\sigma_{u_j}^{-2}) = f_G(\sigma_{u_j}^{-2}|\frac{\tau_j}{2}, \frac{s_{p_j}^2}{2})$. By setting for all j's $\tau_j = 1$ and $s_{p_j}^2 = 0.10$, we are choosing a weak prior on each $\sigma_{u_j}^2$.
- a gamma prior for each $\lambda_j{}^{-1}$, with $j = 1, ..., 14$: $\pi(\lambda_j{}^{-1}) = f_G(\lambda_j{}^{-1}|1, -\ln(r^*))$, where r^* is the prior mean for efficiency. We set r^* equal to 0.875[4].

The full conditional distributions are derived based on the same references as used when choosing the priors:

- $\boldsymbol{\beta}|\text{data}, \mathbf{v}, \Sigma, \boldsymbol{\lambda} \sim N(\bar{\boldsymbol{\beta}}, \bar{\text{H}}^{-1})$, where $\bar{\text{H}} = \text{H}_p + \text{Z}^T\Sigma^{-1}\text{Z}$ and $\bar{\boldsymbol{\beta}} = \bar{\text{H}}^{-1}(\text{H}_p\boldsymbol{\beta}_p + \text{Z}^T\Sigma^{-1}\text{y}^*)$, with $\text{y}^* = \mathbf{y} - \mathbf{v}$.

[1]because as we have seen in the previous chapters and as it is expected, the posterior means of the parameters from the quadratic and interaction terms are smaller than the ones for the linear terms, therefore the variance terms need to be chosen taking that into account. Nevertheless, this is still a relatively uninformative prior considering the observed magnitude of the parameters for this model.

[2]where $f_G(.|\nu_1, \nu_2)$ is a gamma density with mean ν_1/ν_2 and variance ν_1/ν_2^2

[3]following Fernandez, Osiewalski, and Steel (1997)

[4]following Koop, Osiewalski and Steel (1994) and van den Broek, Koop, Osiewalski and Steel (1994).

If we denote $\widehat{\mathrm{H}} = \mathrm{Z}^T\Sigma^{-1}\mathrm{Z}$ and $\widehat{\boldsymbol{\beta}} = (\mathrm{Z}^T\Sigma^{-1}\mathrm{Z})^{-1}\mathrm{Z}^T\Sigma^{-1}\mathbf{y}^*$, then it can be observed that $\bar{\mathrm{H}} = \mathrm{H}_p + \widehat{\mathrm{H}}$ and $\bar{\boldsymbol{\beta}} = \bar{\mathrm{H}}^{-1}[\mathrm{H}_p\boldsymbol{\beta}_p + \widehat{\mathrm{H}}\widehat{\boldsymbol{\beta}}]$. As in the previous chapter, $\widehat{\boldsymbol{\beta}}$ and $\widehat{\mathrm{H}}^{-1}$ are none others than the GLS estimators for the model parameters and variance, which intuitively makes sense for a model with unequal variance.

- $\sigma_{u_j}^{-2}|\text{data}, \sigma_{u_1}^{-2}, ..., \sigma_{u_{j-1}}^{-2}, \sigma_{u_{j+1}}^{-2}, ..., \sigma_{u_{14}}^{-2}, \mathbf{v}, \boldsymbol{\beta}, \lambda$ is gamma distributed with j as the country index: $f_G(\sigma_{u_j}^{-2}|\frac{N_j+\tau-2}{2}, \frac{SSE_j+s_p^2}{2})$, where $SSE_j = (\mathrm{y}_{\mathbf{j}}{}^* - \mathrm{Z}_j\bar{\boldsymbol{\beta}})^T(\mathrm{y}_{\mathbf{j}}{}^* - \mathrm{Z}_j\bar{\boldsymbol{\beta}})$. Z_j is the $N_j \times 140$ matrix obtained from Z, by retaining the rows from $K_{j-1}+1$ to K_j. In other words, $\sigma_{u_j}^2$ for country j will be sampled based on the observations that pertain to it.

- $\lambda_j^{-1}|\text{data}, \lambda_1^{-1}, ..., \lambda_{j-1}^{-1}, \lambda_{j+1}^{-1}, ..., \lambda_{14}^{-1}, \mathbf{v}, \boldsymbol{\beta}, \Sigma$ is gamma distributed: $f_G(\lambda^{-1}|N_j+1, \mathbf{v_j}^T\mathbf{i_{N_j}} - \ln(r^*))$, where $\mathbf{i_{N_j}}$ is a $N_j \times 1$ vector of ones. As before, λ_j for country j will be sampled based on the observations for country j (vector $\mathbf{v}_j$), which are the $K_{j-1}+1$ to K_j elements of the inefficiency vector $\mathbf{v}$.

- $\mathbf{v_j}|\text{data}, \mathbf{v_1}, ..., \mathbf{v_{j-1}}, \mathbf{v_{j+1}}, ..., \mathbf{v_{14}}, \boldsymbol{\beta}, \Sigma, \lambda$ is drawn from a truncated normal distribution[5]: the inefficiency of each bank, $v_{ij} \sim N(y_{ij} - \mathbf{z_i^{N_j}}\boldsymbol{\beta} - \frac{\sigma_{u_j}^2}{\lambda_j}, \sigma_{u_j}^2)\mathrm{I}(v_{ij} > 0)$, where i is the bank-year index, with $i = K_{j-1}+1, ..., K_j$, and j is the country's index. $\mathbf{v_j} = (v_{K_{j-1}+1}, ..., v_{K_j})^T$ is the $N_j \times 1$ inefficiency vector for country j, $\mathbf{z_i^{N_j}}$ is the i's row of the Z matrix and $\mathrm{I}(v_{ij}) > 0$ is an indicator function that takes the value one if $v_{ij} > 0$ and zero otherwise.

For all the results reported in this study we used 5,000 burn in samples and 55,000 Markov Chain Monte Carlo iterations. As a start up values, we use a vector of relatively small inefficiency parameters: $\mathbf{v^{[0]}} = [0.5\ 0.5\ ...\ 0.5]^T$, where $\mathbf{v}$ is of dimension $N \times 1$ and low ${\sigma_{u_j}^2}^{[0]} = 0.01$.

[5]following Jondrow at al.(1983)

7.3 Empirical Results

The tables of results presented in this section for the translog parameters of the Swiss frontier (Table 7.1), λ (Table 7.3), efficiency scores (Table 7.4), σ^2 (Table 7.5) and economies of scale for the selected large banks (Table 7.2) contain the posterior means, standard deviations and highest density regions for the respective parameter or function of parameters of interest from the individual frontier (M1, chapter 5), the hybrid model (M3) with varying prior strength (for different scale factor values $S = 1$, $S = 10^3$, $S = 10^4$, $S = 10^5$, $S = 10^7$) and the common frontier (M2, chapter 6).

In order to show that the hybrid model is nesting the previous 2 approaches from chapter 5 and chapter 6 we need to point out that as the scale factor S increases, we observe the parameter values moving from one endpoint (M1) to the other (M2). Thus, while going through the results tables, we will pay close attention to first and last pairs of columns. The M1 (individual frontier results, chapter 5) and $S = 1$ (hybrid model with weaker prior) columns should match. Also the $S = 10^7$ column (hybrid model with very strong prior) and M2 column (the countries share a common frontier, chapter 6) should yield virtually the same results.

Besides the overlapping of the endpoints, it is interesting to see how the convergence is progressing and for this reason we included the columns of results for $S = 10^3$, $S = 10^4$, $S = 10^5$.

To visually point out and track the convergence process, we also included graphs for Switzerland's translog parameters (Figure 7.1 through Figure 7.10), economies of scale for the selected large banks (Figure 7.15 through Figure 7.28), λ (Figure 7.29 through Figure 7.42), efficiency score (Figure 7.43 through Figure 7.56) and σ^2 (Figure 7.57 through Figure 7.70).

The convergence graphs structure is threefold as we included:

- posterior marginal densities for the parameter or function of parameters of interest (i.e. λ, economies of scale for the selected large banks) drawn for M1 and $S = 1$ (or $S = 0.1$ in some cases) to show how well they superimpose;

- posterior marginal densities for the parameter or function of parameters of interest drawn for M2 and $S = 10^9$ to show how well they superimpose;

- transition graphs that track the evolution of the posterior means, posterior 5^{th} and 95^{th} quantiles for the parameter or function of parameters of interest as the scale factor S takes the following values 0.1; 1; 1,000; 5,000; 10,000; 25,000; 50,000; 75,000; 100,000; 250,000; 500,000; 750,000; 1,000,000; 10,000,000 and 1,000,000,000. This graph is meant to trace the convergence path. In some cases we observe that as a more informative prior is used (as S increases), even a small suggestion (for small values of the scale factor) that the frontiers might be similar causes sharp movements in the parameter's value. Other times, a very strong prior (scale factor at least equal to 1,000) is needed so that the frontiers are pushed together.

As before, we start the results presentation with a look at the technology parameters. For practical reasons we include just the Swiss frontier[6] table results (Table 7.1) and figures (Figure 7.1 through Figure 7.10).

In the table we can observe that the M1 (national frontier) results column and the M3 with weaker prior ($S = 1$) column are virtually identical. The same is true for the last 2 columns that contain the results for M3 with very strong prior ($S = 10^7$) and for M2 (common frontier), the results are nearly identical.

[6]results tables and graphs for the remaining countries' technology parameters are available upon request.

Table 7.1: Translog Parameters: Posterior Means, Standard Deviation,and 90% H.D.R.* - Switzerland

Parameters	M_1 $^\diamond$	$S^\dagger = 1$	$S = 10^3$	$S = 10^4$	$S = 10^5$	$S = 10^7$	M_2
β_1	0.9185	0.9125	1.1090	1.3050	1.4470	1.4400	1.4410
Post. S.D.	(0.1169)	(0.1152)	(0.0695)	(0.0349)	(0.0282)	(0.0236)	(0.0234)
$[H.D.R.]$	[0.728,1.113]	[0.725,1.104]	[0.996,1.223]	[1.248,1.363]	[1.398,1.492]	[1.401,1.479]	[1.403,1.480]
β_2	0.1686	0.1688	0.1661	0.2560	0.4002	0.4425	0.4431
Post. S.D.	(0.0652)	(0.0650)	(0.0452)	(0.0273)	(0.0258)	(0.0194)	(0.0192)
$[H.D.R.]$	[0.062,0.277]	[0.063,0.276]	[0.092,0.241]	[0.211,0.301]	[0.353,0.438]	[0.411,0.474]	[0.411,0.475]
β_3	0.1287	0.1285	0.1186	0.0886	0.0698	0.0547	0.0542
Post. S.D.	(0.0115)	(0.0114)	(0.0093)	(0.0064)	(0.0047)	(0.0047)	(0.0047)
$[H.D.R.]$	[0.120,0.148]	[0.120,0.147]	[0.103,0.134]	[0.078,0.099]	[0.062,0.078]	[0.047,0.062]	[0.047,0.062]
β_4	0.3592	0.3618	0.3302	0.3143	0.3731	0.4728	0.4753
Post. S.D.	(0.0516)	(0.0512)	(0.0342)	(0.0204)	(0.0149)	(0.0119)	(0.0118)
$[H.D.R.]$	[0.274,0.444]	[0.277,0.445]	[0.274,0.386]	[0.281,0.348]	[0.348,0.397]	[0.454,0.493]	[0.456,0.495]
β_5	0.0520	0.0522	0.0460	0.0364	0.0403	0.0476	0.0478
Post. S.D.	(0.0058)	(0.0058)	(0.0050)	(0.0039)	(0.0036)	(0.0020)	(0.0020)
$[H.D.R.]$	[0.042,0.062]	[0.042,0.062]	[0.038,0.054]	[0.030,0.043]	[0.034,0.046]	[0.044,0.051]	[0.045,0.051]
β_6	0.1464	0.1457	0.2514	0.3688	0.3957	0.3561	0.3536
Post. S.D.	(0.0399)	(0.0401)	(0.0336)	(0.0207)	(0.0156)	(0.0087)	(0.0087)
$[H.D.R.]$	[0.082,0.213]	[0.080,0.212]	[0.196,0.307]	[0.335,0.403]	[0.372,0.423]	[0.342,0.371]	[0.340,0.368]
β_7	-0.0052	-0.0052	-0.0059	-0.0019	0.0172	0.0266	0.0269
Post. S.D.	(0.0027)	(0.0026)	(0.0028)	(0.0027)	(0.0022)	(0.0010)	(0.0010)
$[H.D.R.]$	[-0.010,-0.001]	[-0.010,-0.001]	[-0.010,-0.001]	[-0.006,0.003]	[0.014,0.021]	[0.025,0.028]	[0.025,0.028]
β_8	-0.0222	-0.0225	-0.0313	-0.0538	-0.0687	-0.0851	-0.0856
Post. S.D.	(0.0184)	(0.0183)	(0.0135)	(0.0082)	(0.0058)	(0.0058)	(0.0057)
$[H.D.R.]$	[-0.053,0.008]	[-0.053,0.008]	[-0.054,-0.009]	[-0.067,-0.040]	[-0.078,-0.059]	[-0.095,-0.076]	[-0.095,-0.076]
β_9	-0.0049	-0.0040	-0.0513	-0.0920	-0.0827	-0.0564	-0.0555
Post. S.D.	(0.0177)	(0.0176)	(0.0143)	(0.0080)	(0.0048)	(0.0041)	(0.0041)
$[H.D.R.]$	[-0.034,0.024]	[-0.033,0.025]	[-0.075,-0.028]	[-0.105,-0.079]	[-0.091,-0.075]	[-0.063,-0.050]	[-0.062,-0.049]
β_{10}	-0.0730	-0.0730	-0.0882	-0.1007	-0.0721	-0.0545	-0.0540
Post. S.D.	(0.0085)	(0.0085)	(0.0076)	(0.0058)	(0.0055)	(0.0029)	(0.0029)
$[H.D.R.]$	[-0.087,-0.059]	[-0.087,-0.059]	[-0.101,-0.076]	[-0.110,-0.091]	[-0.083,-0.064]	[-0.059,-0.050]	[-0.059,-0.049]

Notes: $*$ Highest Density Region.
$\diamond$ Based on national frontiers (M1).
$\dagger S^i$ stands for a scale factor of order 10^i.
Posterior moments are computed based on 50,000 points generated from the Gibbs sampling algorithm. The end points of the 90% confidence region are the 5^{th} and the 95^{th} percentiles of the posterior marginal densities.

The results columns for the hybrid model (M3) with $S = 10^3$, $S = 10^4$, $S = 10^5$ show almost direct[7] convergence for the parameters β_1, β_2, β_3, β_7, β_8 and indirect[8] convergence for β_4, β_5, β_6, β_9 and β_{10}.

While results table tell the convergence story, the figures 7.1 through 7.10 are even more convincing. Each picture includes 3 plots. On the one hand we superimposed the posterior marginal densities for M1 and M3 with weak prior ($S = 1$) and on the other hand, we superimposed the posterior marginal densities for M2 and M3 with very strong prior ($S = 10^9$). Both plots show perfect overlapping, confirming that the models convergence.

The transition graphs, drawn for different strength levels of the prior add interesting information to the convergence story, as they confirm direct convergence for parameters: β_1 (Figure 7.1), β_2 (Figure 7.2), β_3 (Figure 7.3), β_7 (Figure 7.7) and β_8 (Figure 7.8). In the case of the translog parameters β_4 (Figure 7.4), β_5 (Figure 7.5), β_6 (Figure 7.10), β_9 (Figure 7.9) and β_{10} (Figure 7.10), the convergence is indirect.

The transition graphs also point out a previously mentioned idea: the posterior highest density regions of the parameters are generally wider for model M1 than for model M2 for the majority of the countries[9], especially for the ones with very small number of observations.

Another thing to note about the transition graphs of the translog parameters for the Swiss frontier is that the convergence process seems to be slow (it takes strong priors to get the movement from M1 towards M2). Since it takes a strong prior to push the Swiss frontier towards the common frontier, it follows that there is strong evidence in the data that Switzerland has a different frontier than the common frontier.

[7] whenever the parameter's estimates from the hybrid model remain within the bounds of the M1 and M2 results as the prior's strength is varied, we will call it direct convergence.

[8] if the parameter's estimates from the hybrid model overshoot or drop below the margins defined by the M1 and M2 results as the prior's strength is varied, we will call it indirect convergence.

[9] less so for Germany as it has more than half of the sample's observations

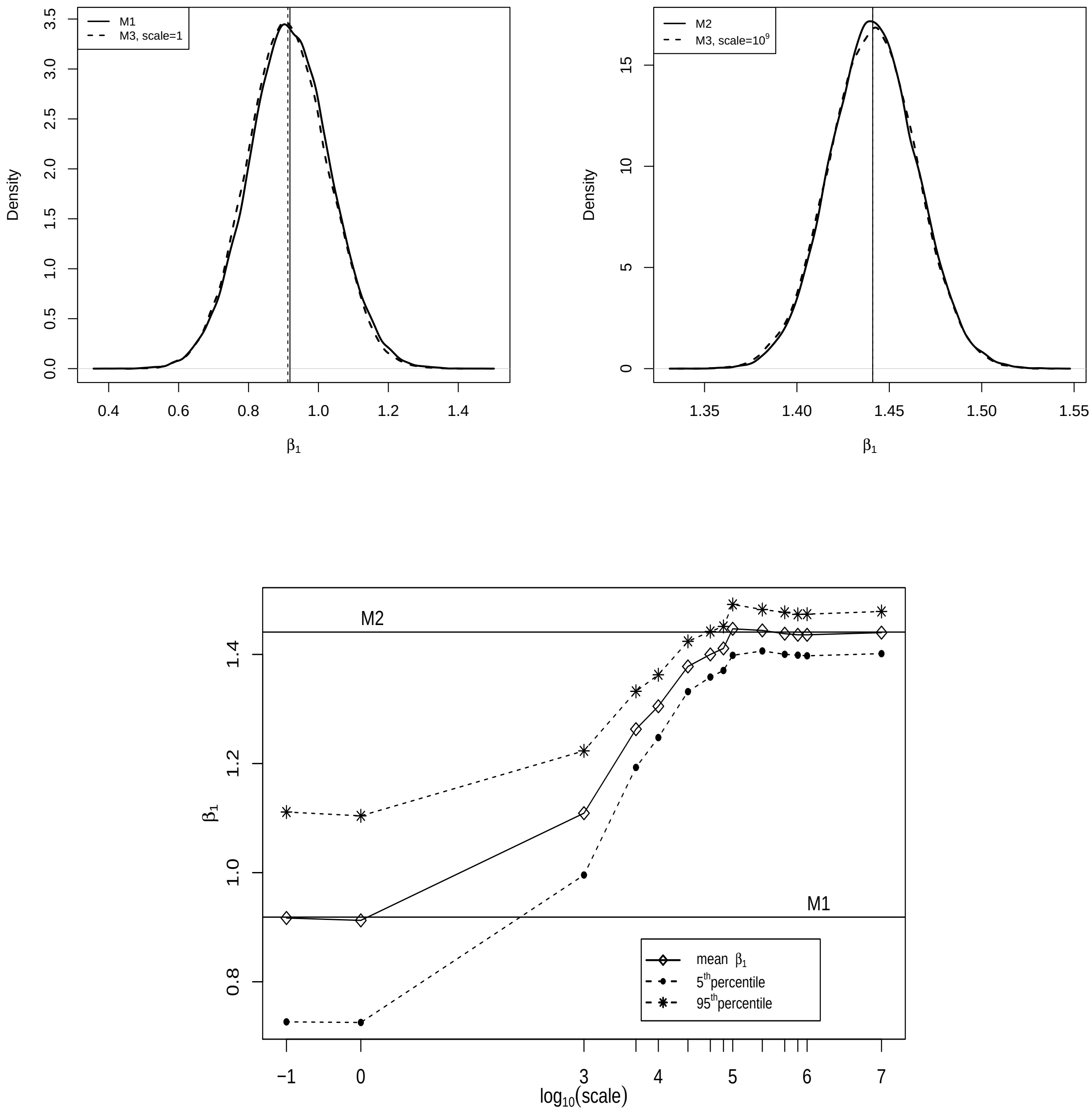


Figure 7.1: Switzerland - Model Convergence, Translog Parameters: β_1.

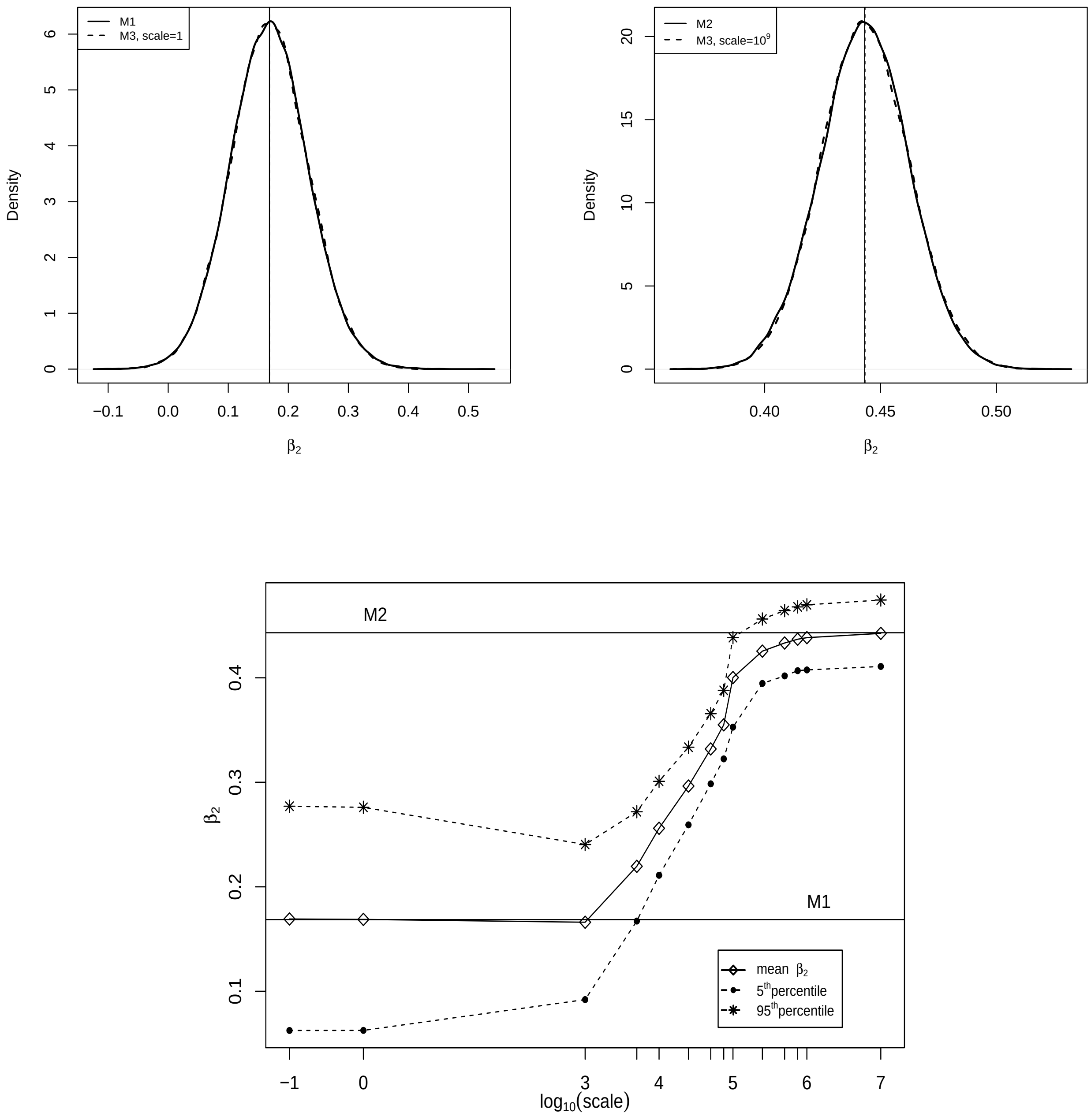


Figure 7.2: Switzerland - Model Convergence, Translog Parameters: β_2.

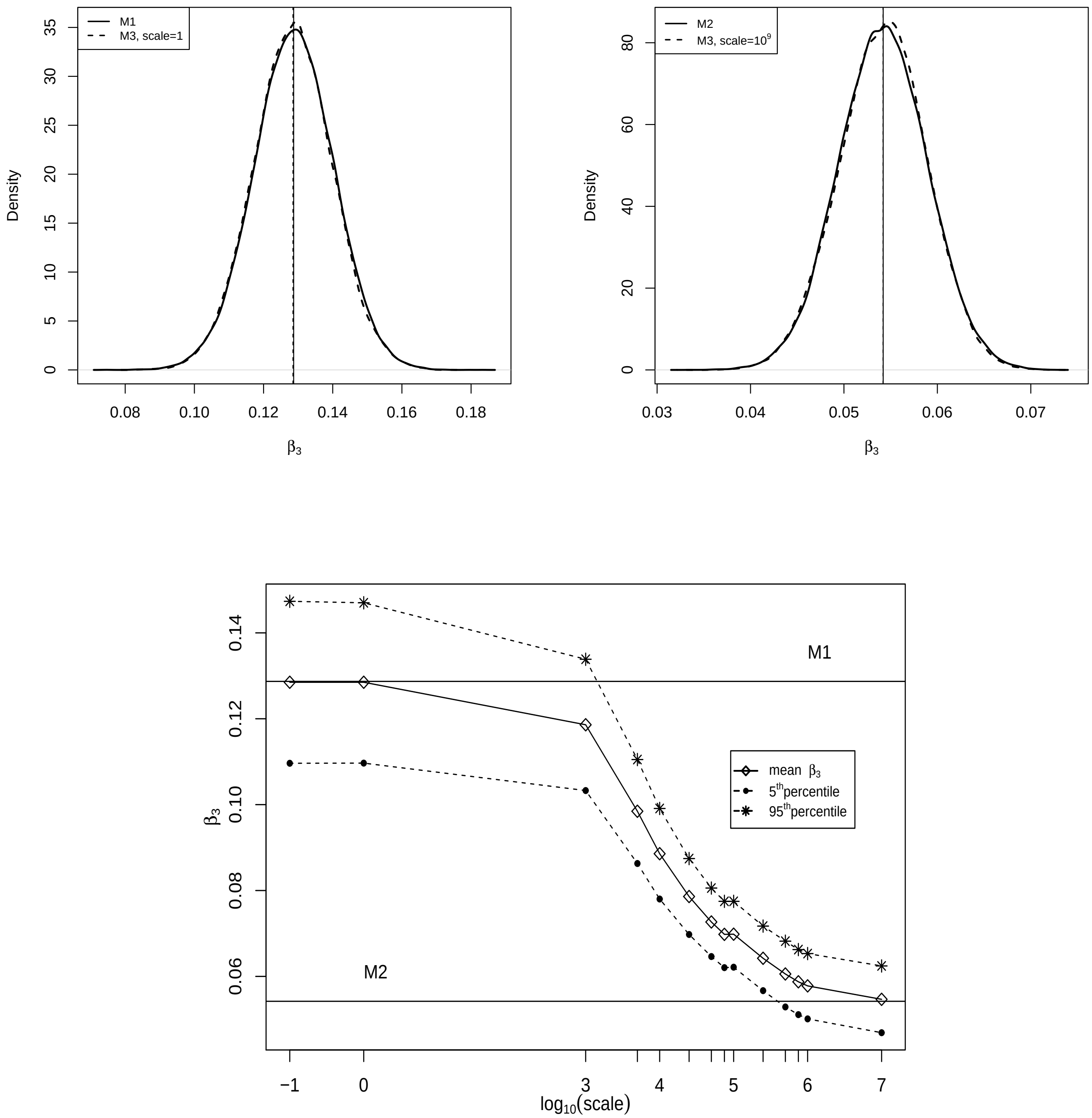


Figure 7.3: Switzerland - Model Convergence, Translog Parameters: β_3.

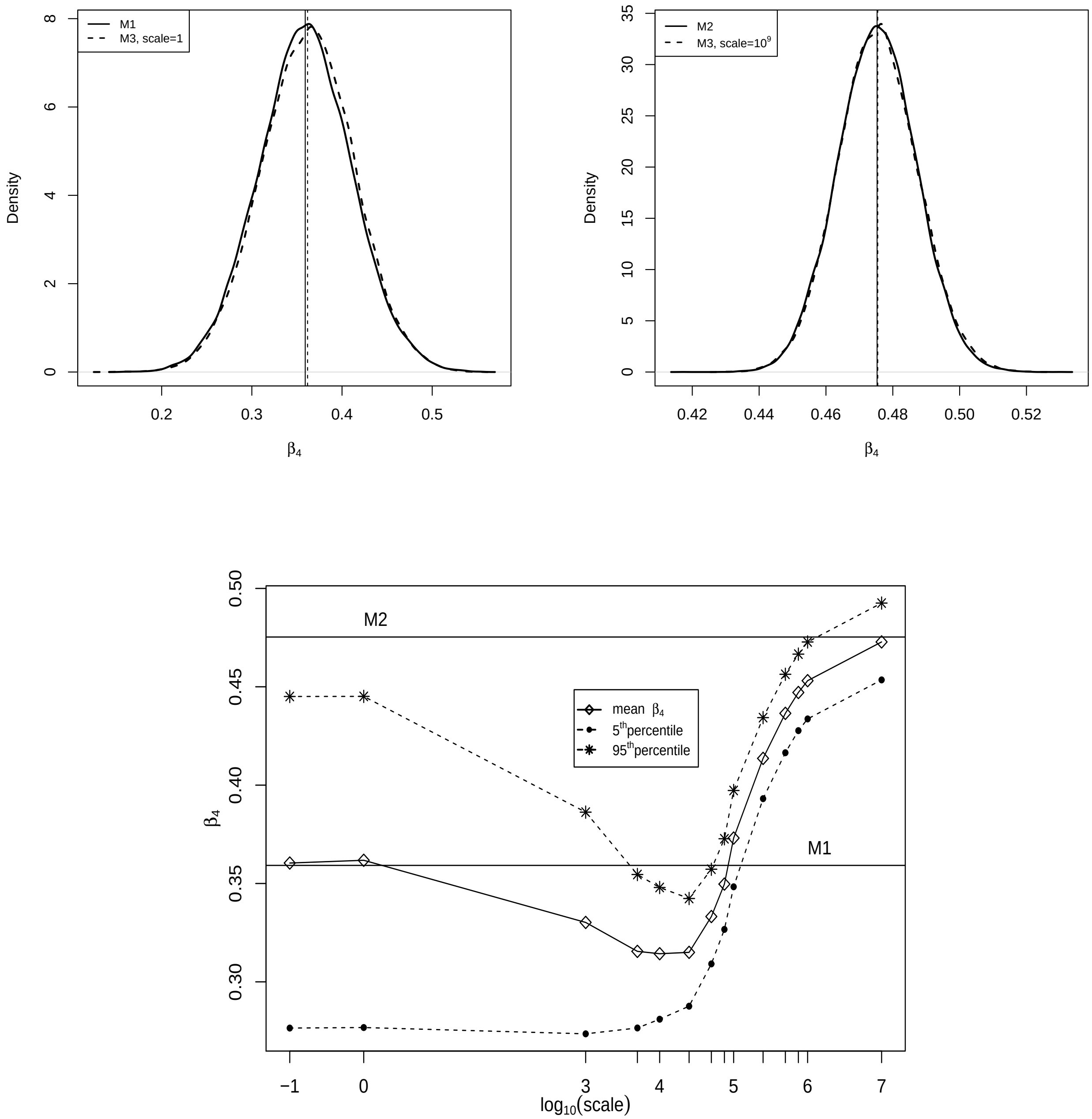


Figure 7.4: Switzerland - Model Convergence, Translog Parameters: β_4.

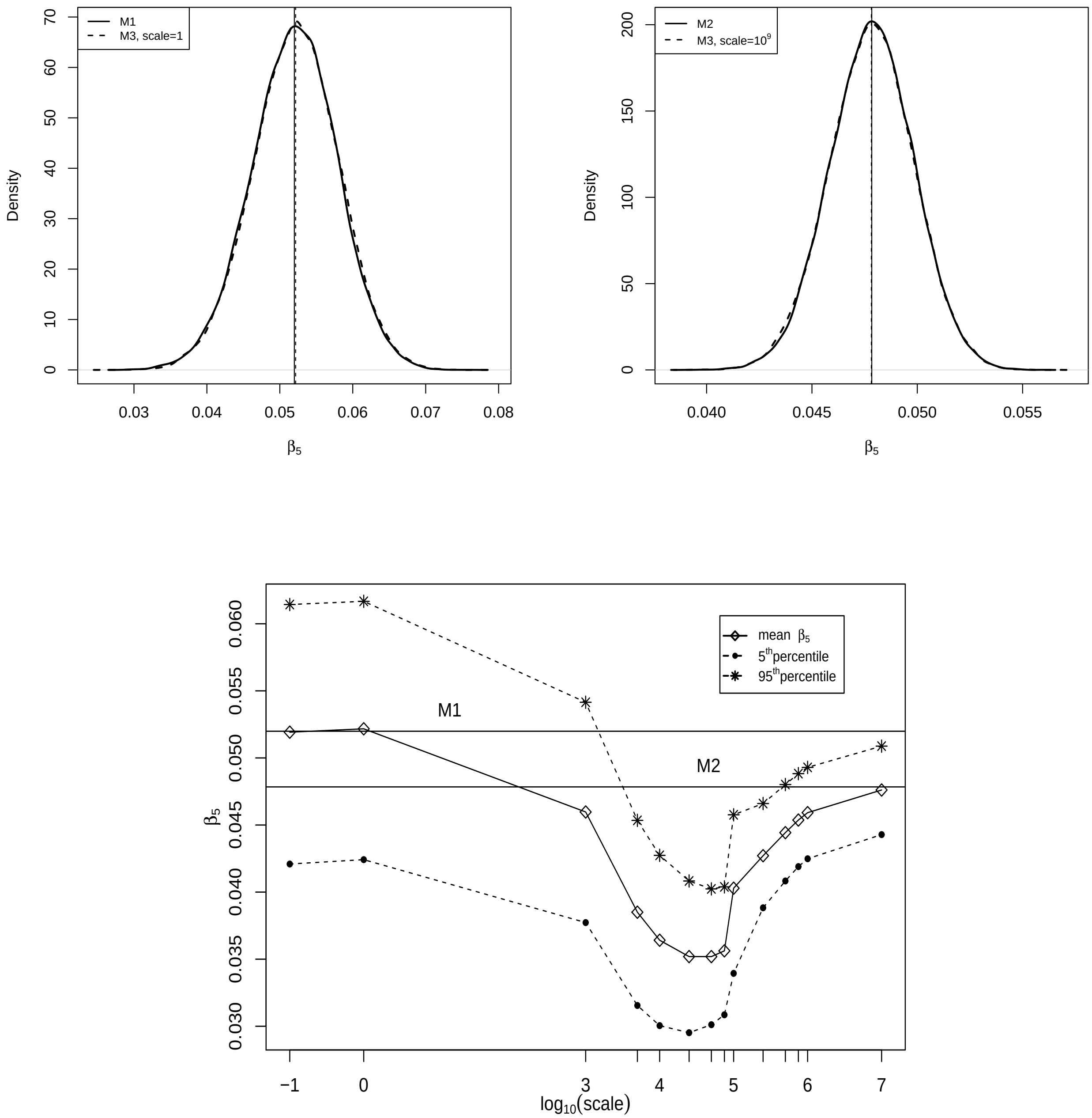


Figure 7.5: Switzerland - Model Convergence, Translog Parameters: β_5.

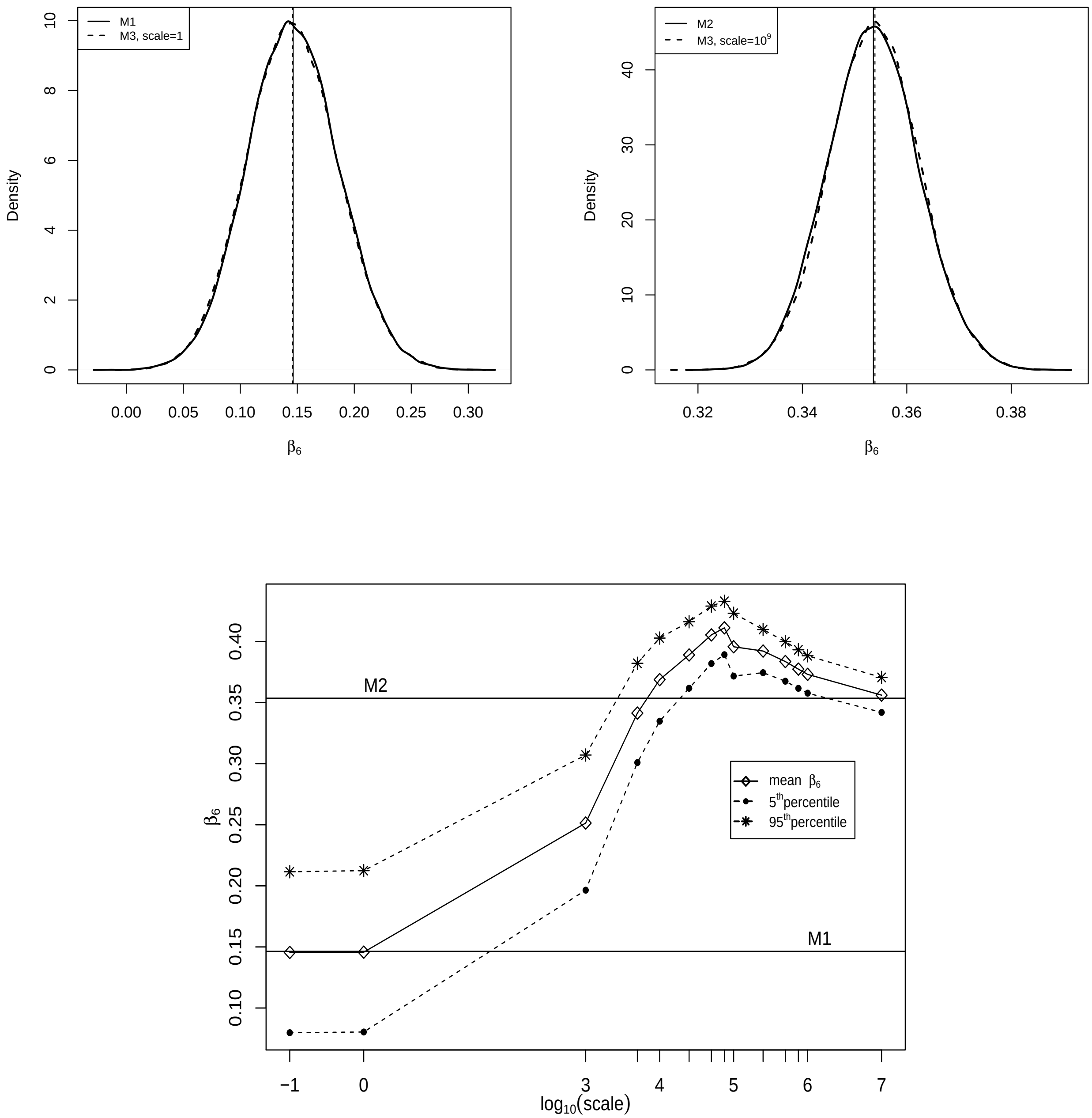


Figure 7.6: Switzerland - Model Convergence, Translog Parameters: β_6.

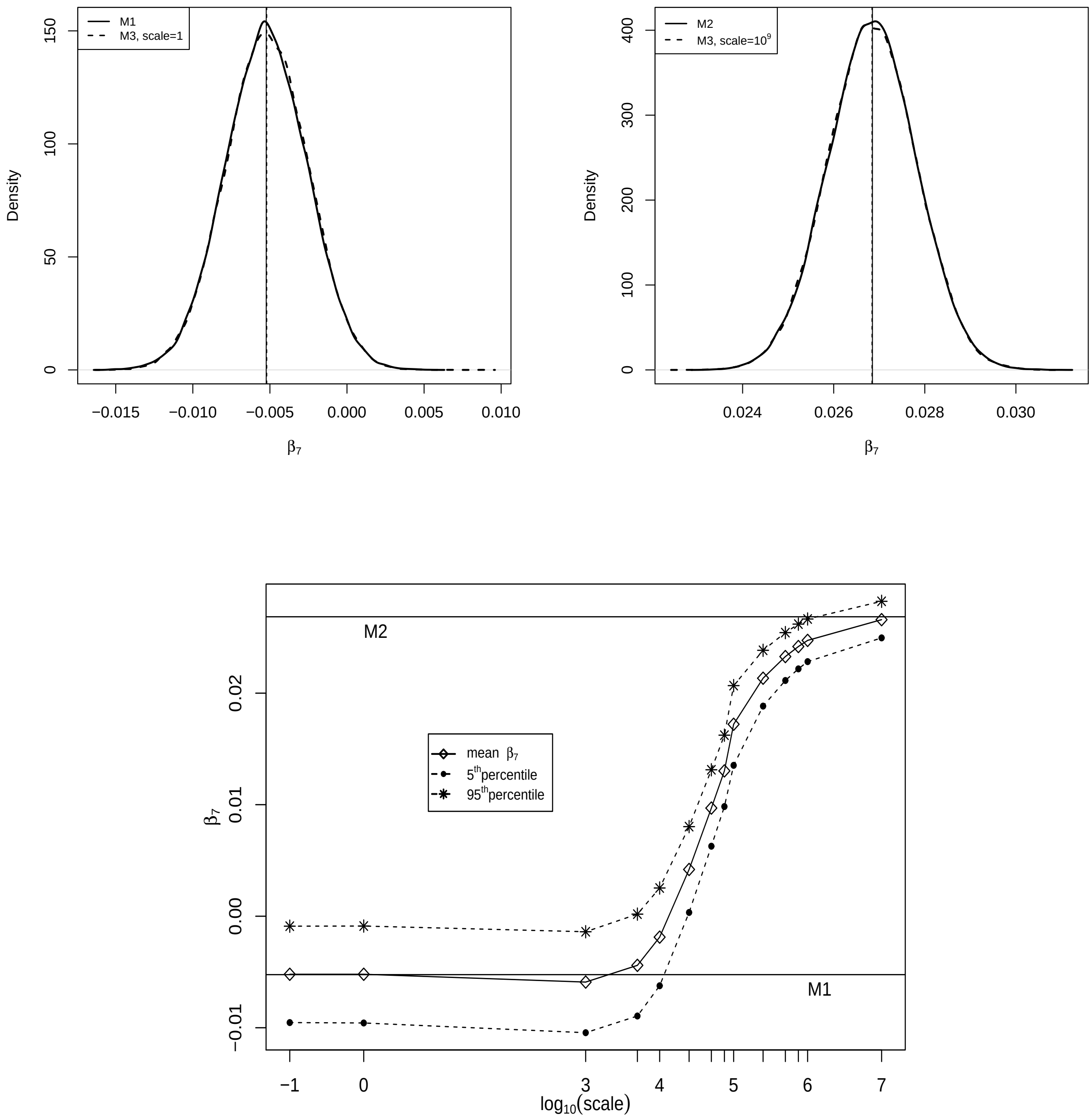


Figure 7.7: Switzerland - Model Convergence, Translog Parameters: β_7.

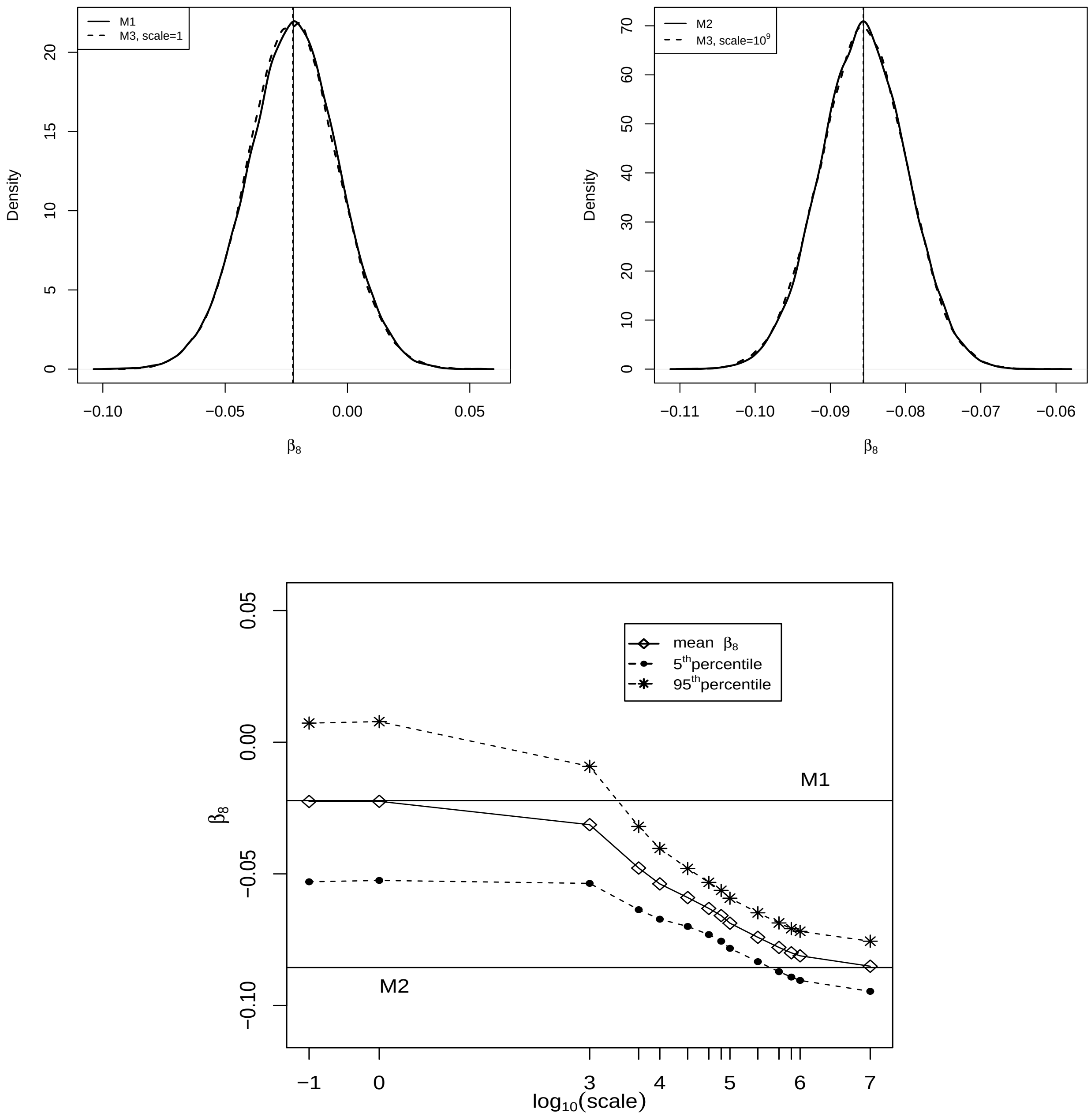


Figure 7.8: Switzerland - Model Convergence, Translog Parameters: β_8.

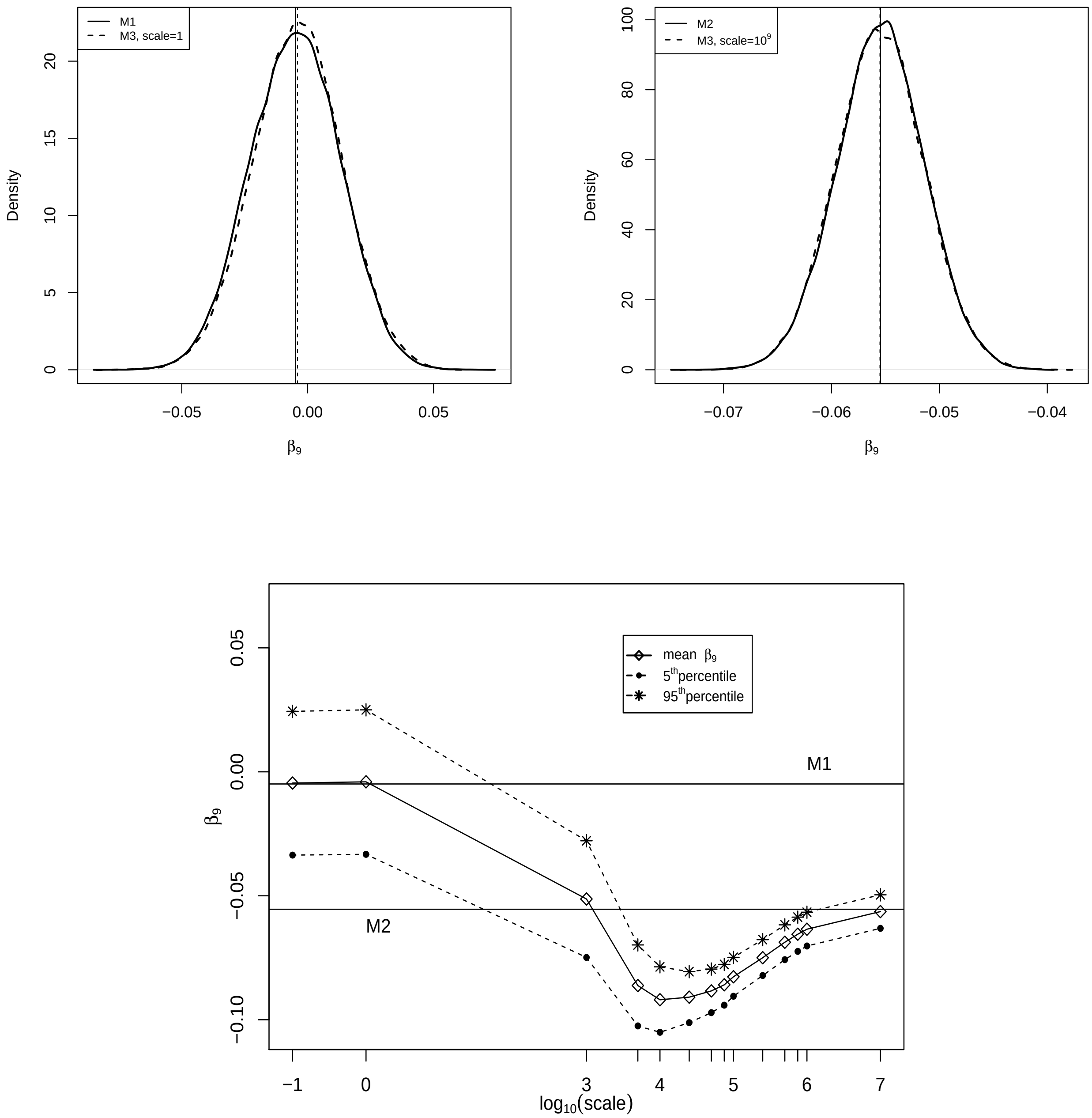


Figure 7.9: Switzerland - Model Convergence, Translog Parameters: β_9.

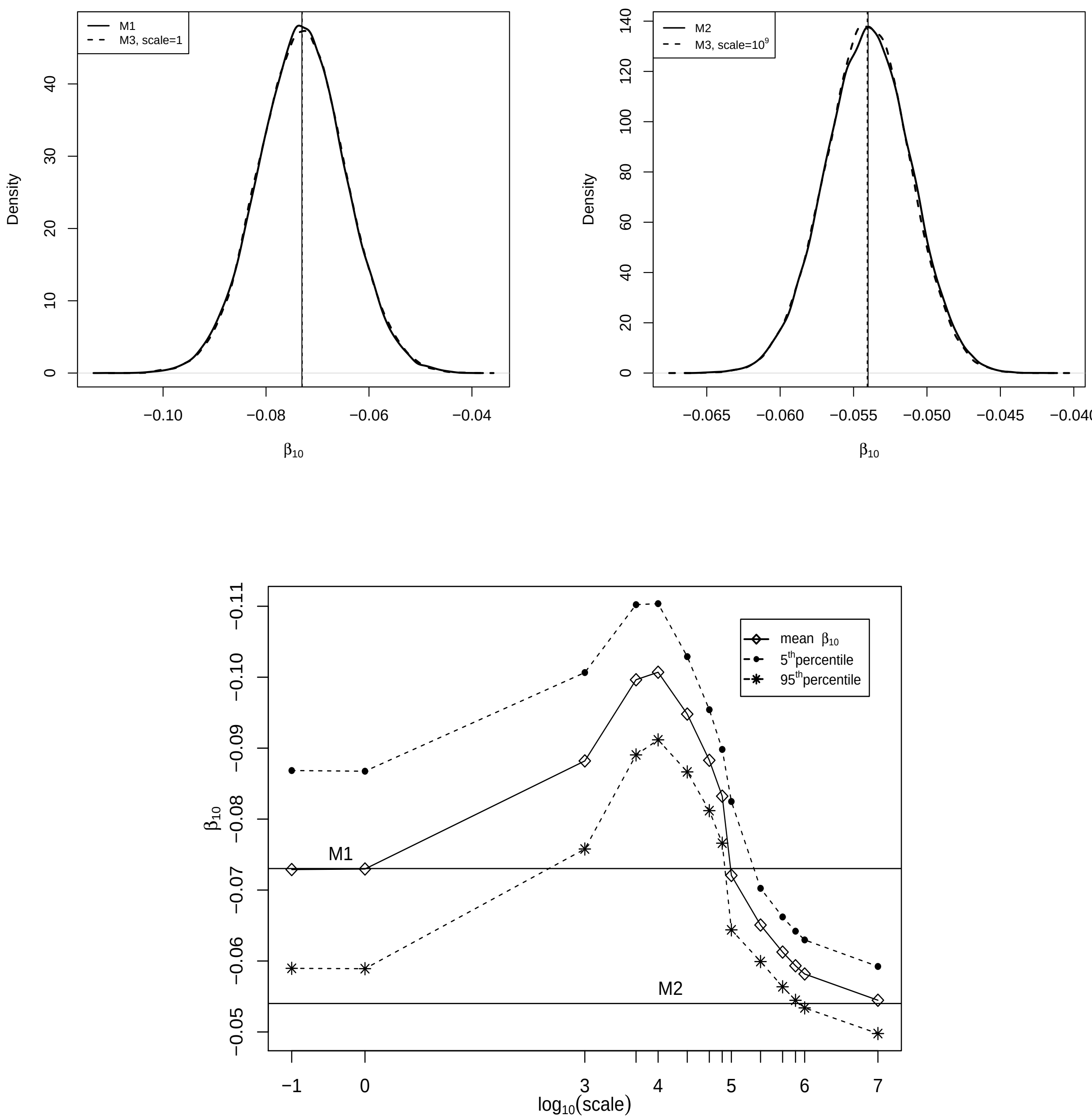


Figure 7.10: Switzerland - Model Convergence, Translog Parameters: β_{10}.

Figures 7.11 through 7.14 offer a better understanding of the role that the priors have in the hybrid model. As previously, we have drawn cost frontiers for a few countries (Switzerland, Germany, Italy and France) by holding loan/equity and security/equity constant at the median values of the pooled dataset, and varying avwage/avrate between its minimum and maximum values, and this time we did it for M3 at different values of the prior ($S = 1$, $S = 10^3$, $S = 10^5$ and $S = 5 \times 10^5$). As the strength of the prior increases (higher S), we can see how frontiers are pushed together. When it comes to the shape of the frontiers, it should be mentioned that the concavity property of the cost function is violated by most of the frontiers depicted here. Also, it is apparent that for the chosen countries it takes a very strong prior ($S = 10^5$) to get their frontiers close.

To complement the analysis of the translog parameters, we have calculated the economies of scale for the same select group of large banks at different values of the prior. Table 7.2 contains the posterior means, standard deviations and highest density regions for the economies of scale obtained with M1, M2 and M3 (at scale factor $S = 1$, $S = 10^3$, $S = 10^5$ and $S = 10^7$). The columns for M1 and M3 with uninformative prior ($S = 1$) are almost the same. M2 and M3 with very informative prior ($S = 10^7$) also look very much alike. A more complete image of the convergence is captured by figures 7.15 through 7.28. In the case of the Slovenian, Serbian, Romanian and Dutch banks we notice that the posterior marginal densities for economies of scale do not overlap perfectly in the case of M1 and M3 with weak prior. Since M1 is defined as a model with a diffuse prior on the translog parameters while M2 and M3 are both set up as models with normal priors on the β's, it is more likely to find small discrepancies in the case of M1 and M3.

The transition graphs also offer information about the convergence path. We observe direct convergence in the case of the Danish (Figure 7.16), German (Figure 7.18), Dutch (Figure 7.20), Polish (Figure 7.21), Romanian (Figure 7.22), Serbian (Figure 7.23) and Turkish (Figure 7.27) banks.

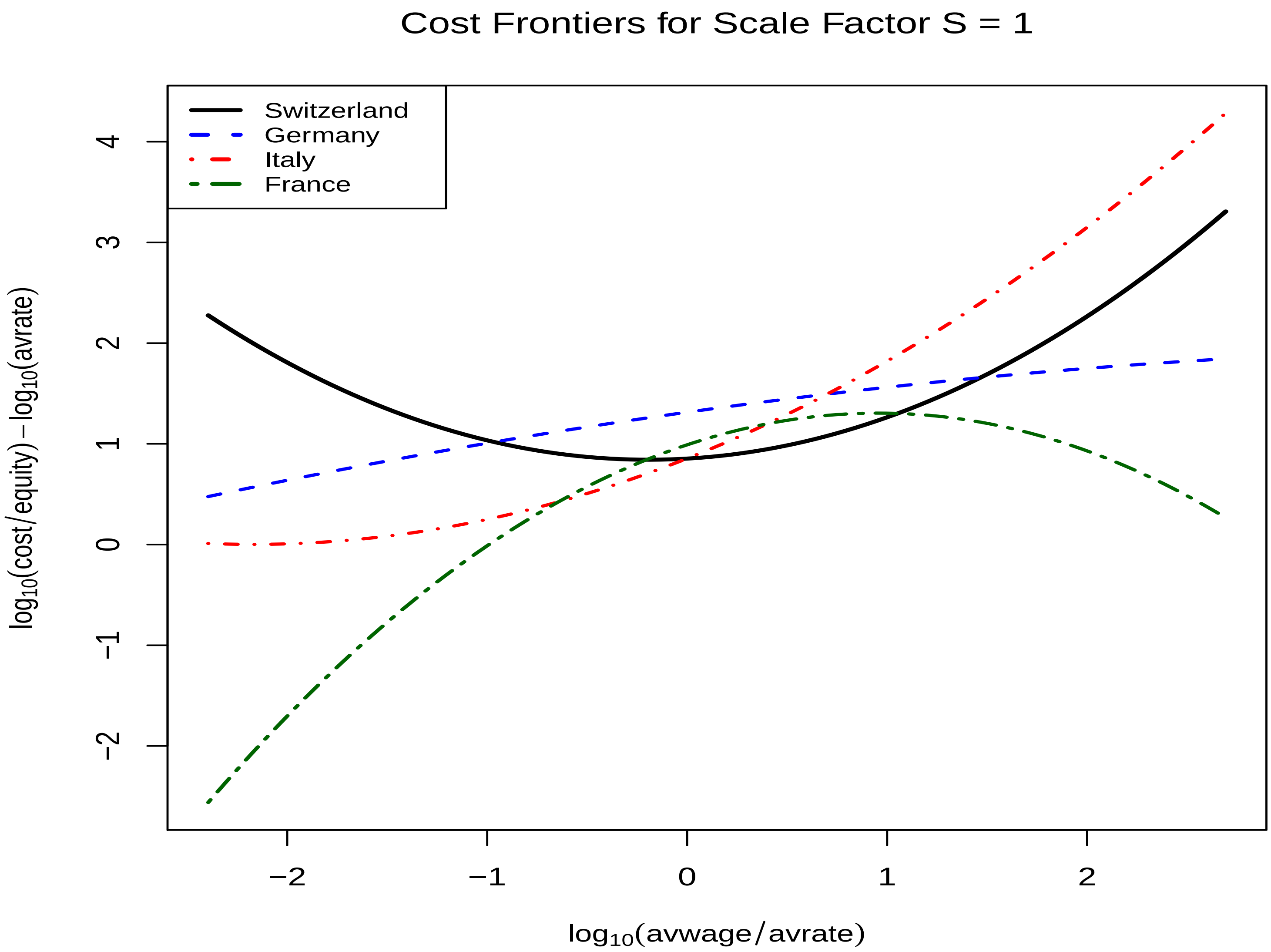


Figure 7.11: Swiss, German, Italian and French Frontiers Drawn for $S = 1$ at the Sample Median Values for loan/equity and security/equity.

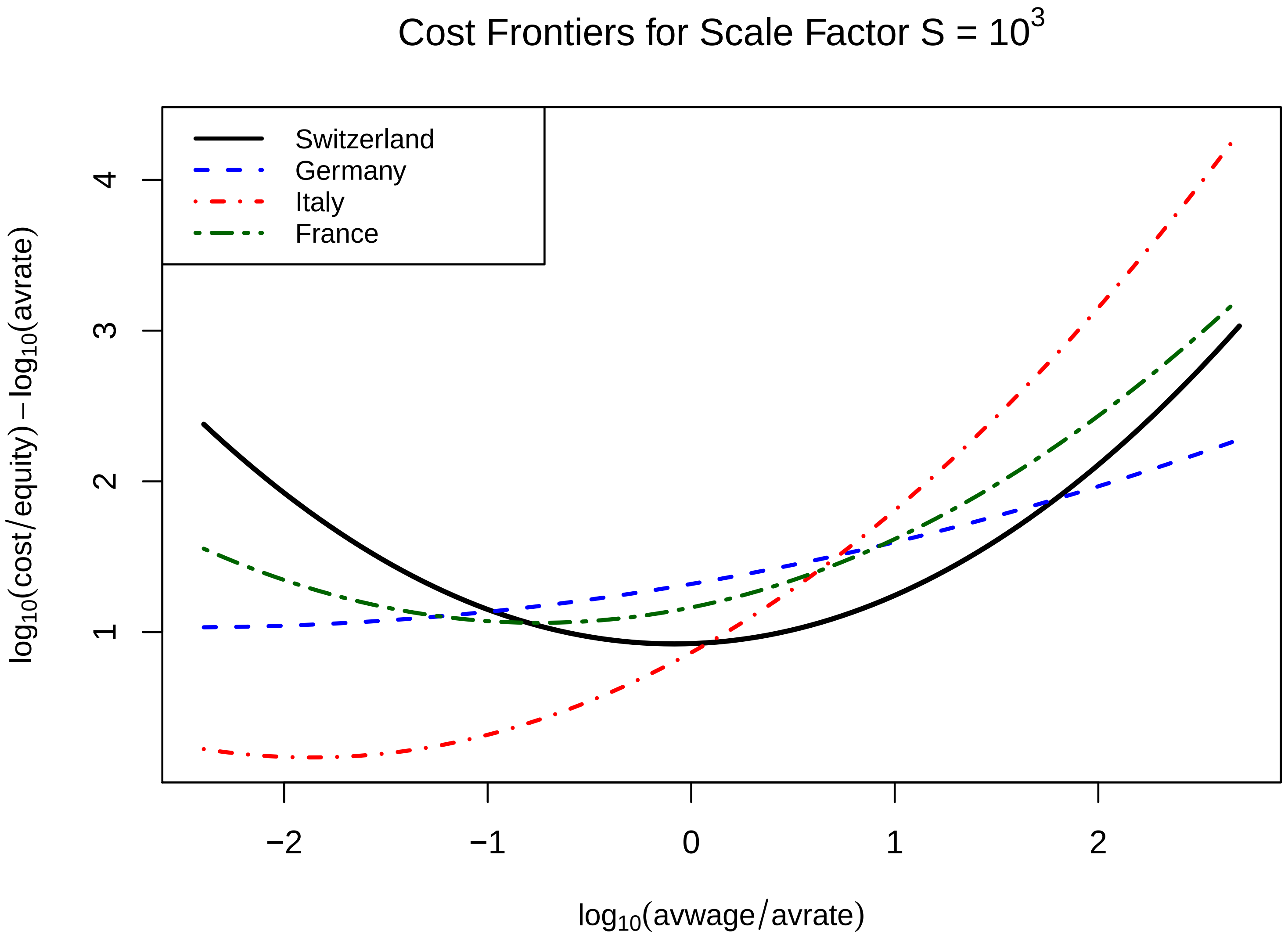


Figure 7.12: Swiss, German, Italian and French Frontiers Drawn for $S = 10^3$ at the Sample Median Values for loan/equity and security/equity.

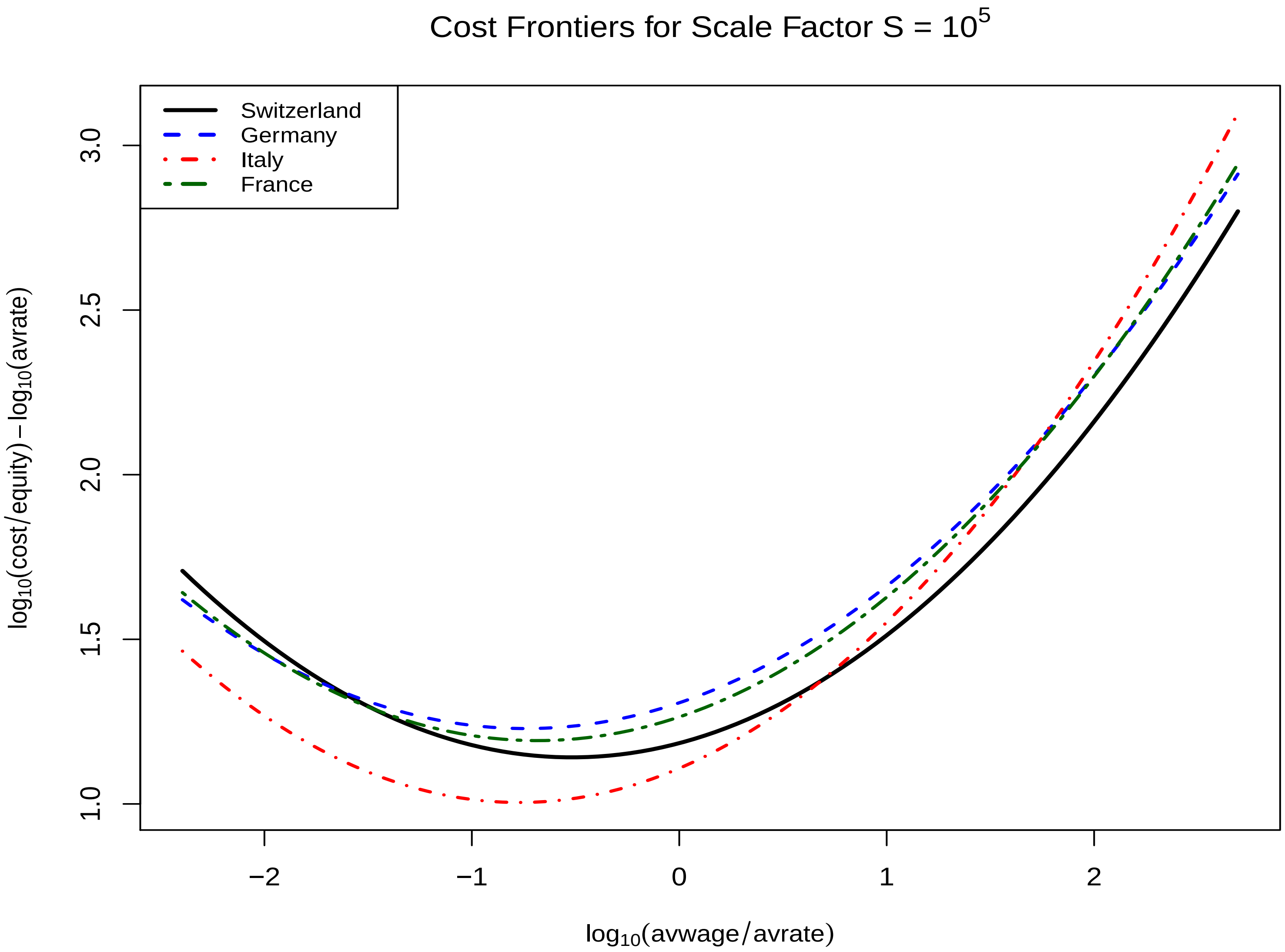


Figure 7.13: Swiss, German, Italian and French Frontiers Drawn for $S = 10^5$ at the Sample Median Values for loan/equity and security/equity.

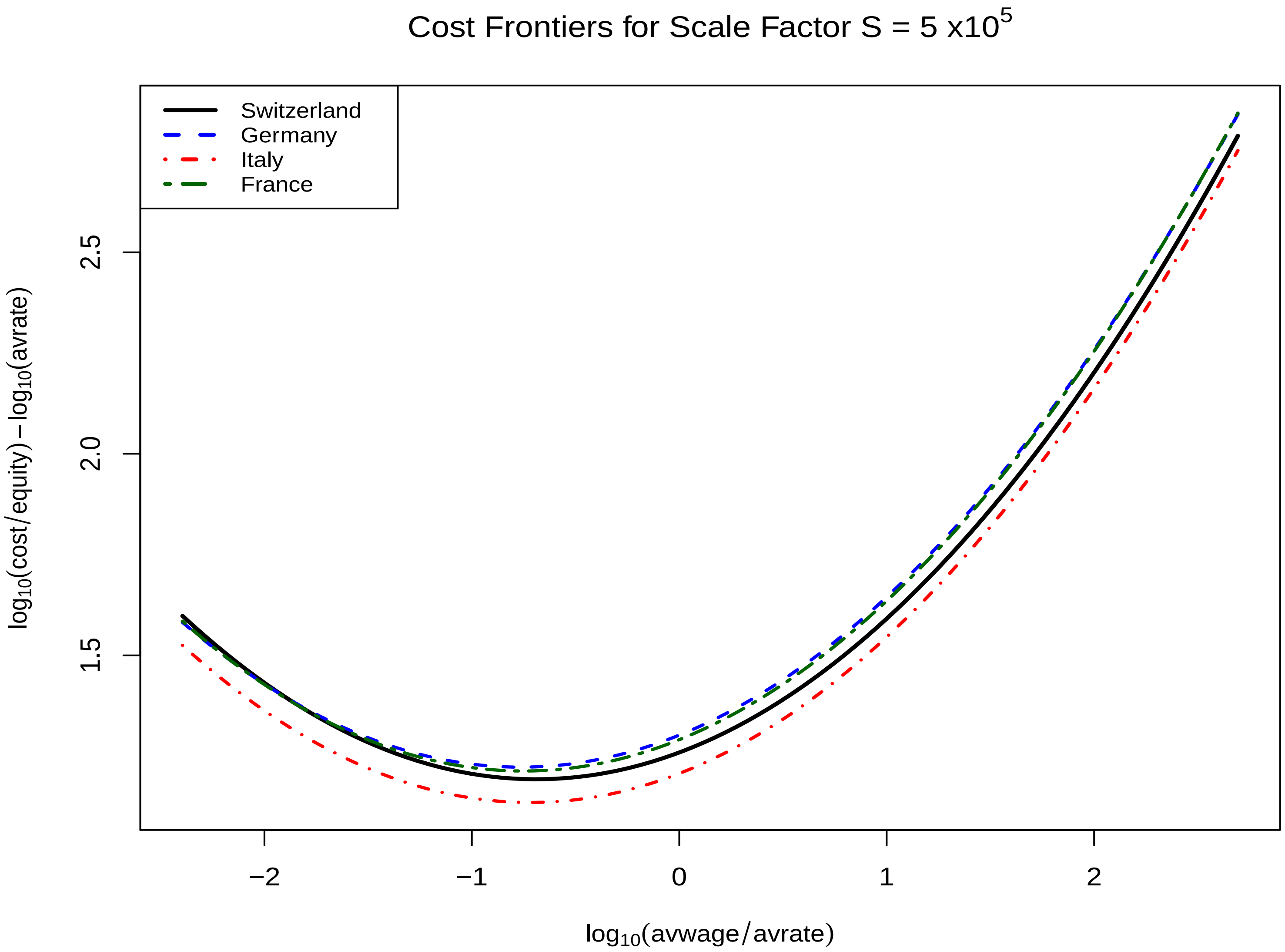


Figure 7.14: Swiss, German, Italian and French Frontiers Drawn for $S = 5 \times 10^5$ at the Sample Median Values for loan/equity and security/equity.

Table 7.2: Economies of Scale for Selected Banks: Posterior Means, Standard Deviation, 90% H.D.R.*

Bank name	$M_1^{\diamond}$	$S = 1$	$S = 10^3$	$S = 10^5$	$S = 10^7$	M_2°
Hrvatska Postanska	1.063	1.081	1.021	1.109	1.132	1.132
Post. S.D.	0.2428	0.241	0.09303	0.02763	0.01073	0.01032
[*H.D.R.*]	[0.7811,1.485]	[0.7965,1.51]	[0.8837,1.185]	[1.064,1.156]	[1.114,1.149]	[1.116,1.15]
Skandinaviska Enskilda	0.9475	0.9457	1.074	1.711	1.784	1.786
Post. S.D.	0.09868	0.09823	0.08821	0.06386	0.03492	0.0349
[*H.D.R.*]	[0.7987,1.122]	[0.7976,1.118]	[0.9418,1.23]	[1.606,1.816]	[1.728,1.842]	[1.729,1.844]
Banque Populaire des Alpes	1.259	1.261	1.204	1.276	1.338	1.339
Post. S.D.	0.08915	0.09021	0.07212	0.04272	0.02203	0.02182
[*H.D.R.*]	[1.122,1.414]	[1.123,1.418]	[1.093,1.328]	[1.206,1.347]	[1.303,1.375]	[1.304,1.376]
Thüringer Aufbaubank	1.201	1.201	1.193	1.148	1.137	1.137
Post. S.D.	0.01464	0.01465	0.01393	0.01188	0.01172	0.01172
[*H.D.R.*]	[1.177,1.225]	[1.177,1.226]	[1.171,1.217]	[1.129,1.168]	[1.118,1.156]	[1.118,1.156]
Banca Monte Parma	0.9814	0.9812	1.018	1.722	1.263	1.249
Post. S.D.	0.02179	0.02184	0.02341	0.0484	0.01207	0.0113
[*H.D.R.*]	[0.9463,1.018]	[0.9462,1.018]	[0.9806,1.058]	[1.646,1.804]	[1.243,1.283]	[1.231,1.268]

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Bank name	$M_1^{\diamond}$	$S = 1$	$S = 10^3$	$S = 10^5$	$S = 10^7$	M_2°
Staalbankiers NV	2.568	2.568	2.073	1.475	1.42	1.42
Post. S.D.	0.8202	0.7356	0.3308	0.05195	0.01792	0.01743
[*H.D.R.*]	[1.771,3.814]	[1.768,3.822]	[1.63,2.677]	[1.392,1.563]	[1.391,1.45]	[1.392,1.449]
Bank BPH SA	1.101	1.113	1.275	1.272	1.287	1.287
Post. S.D.	0.1907	0.1939	0.1321	0.03197	0.0109	0.01053
[*H.D.R.*]	[0.8511,1.447]	[0.8604,1.463]	[1.083,1.512]	[1.221,1.326]	[1.269,1.305]	[1.27,1.305]
Banca Romaneasca	1.596	1.597	1.245	1.001	1.035	1.036
Post. S.D.	0.6646	0.5953	0.1552	0.03276	0.01702	0.01677
[*H.D.R.*]	[1.061,2.471]	[1.065,2.454]	[1.022,1.524]	[0.9483,1.056]	[1.007,1.063]	[1.009,1.064]
AIK Banka ad Nis	1.821	1.835	1.233	1.015	1.039	1.041
Post. S.D.	0.8483	2.186	0.1567	0.0307	0.02104	0.02099
[*H.D.R.*]	[1.154,2.921]	[1.163,2.91]	[1.011,1.515]	[0.9639,1.065]	[1.005,1.074]	[1.006,1.075]
Gorenjska Banka d.d. Kranj	0.8467	0.8634	1.186	1.233	1.225	1.226
Post. S.D.	0.2716	0.3299	0.08482	0.02757	0.01306	0.01279
[*H.D.R.*]	[0.5845,1.263]	[0.5976,1.281]	[1.058,1.336]	[1.188,1.279]	[1.203,1.246]	[1.205,1.247]
Färs & Frosta Sparbank	1.348	1.34	1.237	1.465	1.467	1.467
Post. S.D.	0.1112	0.1093	0.07263	0.04534	0.01979	0.01946
[*H.D.R.*]	[1.183,1.544]	[1.179,1.534]	[1.125,1.363]	[1.391,1.54]	[1.435,1.5]	[1.435,1.499]

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Bank name	M_1 ◊	$S = 1$	$S = 10^3$	$S = 10^5$	$S = 10^7$	M_2 ∘
ABN Amro Bank (Schweiz) AG	2.427	2.406	2.843	2.028	1.562	1.556
Post. S.D.	0.225	0.2177	0.2742	0.08605	0.01726	0.01669
[*H.D.R.*]	[2.098,2.831]	[2.09,2.799]	[2.441,3.329]	[1.9,2.181]	[1.534,1.591]	[1.529,1.584]
Anadolubank	1.666	1.666	1.448	0.9813	0.9471	0.9476
Post. S.D.	0.41	0.4183	0.1844	0.02334	0.01443	0.01422
[*H.D.R.*]	[1.2,2.372]	[1.2,2.37]	[1.185,1.78]	[0.9436,1.02]	[0.9235,0.9709]	[0.9246,0.9712]
JP Morgan Intl. Bank Ltd	1.58	1.587	1.744	1.687	1.624	1.623
Post. S.D.	0.1843	0.1846	0.1985	0.07304	0.03318	0.03267
[*H.D.R.*]	[1.316,1.91]	[1.322,1.918]	[1.462,2.101]	[1.573,1.811]	[1.571,1.68]	[1.571,1.678]

Notes: ∗ Highest Density Region
◊ The results were obtained using the national frontier obtained in the previous chapter (model M_1).
∘ The results were obtained using a multiple lambda model (common frontier, allowing for the inefficiencies to differ for each country - model M_2).

Posterior moments are computed based on 50,000 points generated from the Gibbs sampling algorithm. The end points of the 90% confidence region are the 5^{th} and the 95^{th} percentiles of the posterior marginal densities.

For all the other banks (Croatian, Figure 7.15; French, Figure 7.17; Italian, Figure 7.19; Swedish, Figure 7.25; Swiss, Figure 7.26; and British Figure 7.28), the convergence happens indirectly (with the exception of the Italian and Swiss banks). Often, these are banks for which the economies of scale do not change much from M1 to M2 (small range to move within, making overshooting and indirect convergence more likely). The transition plots for the Italian and Swiss banks suggest that probably at those specific levels of outputs and input prices (corresponding to the banks), the Italian and the Swiss cost frontier are very different than the common frontier.

Especially for the countries with a small number of observations (Romania, Turkey, Serbia, etc.), we can easily see on the transition plots that the posterior highest density regions that accompany model M1 results are wider than the ones obtained from M2 for the economies of scale.

Another thing to notice about most of the countries with a small number of observations (Poland, Romania, Netherlands, Serbia, Slovenia, Denmark) is that there are rapid adjustments in the values of the economies of scale for relatively weak priors. In other words, the economies of scale for these countries seem to be sensitive to the prior's strength and convergence is faster when the data provides less information.

Because of the high number of observations that we have from Germany, the relatively rapid convergence for the economies of scale of the large bank could be considered a sign that at that particular level of input prices and outputs, the German frontier is close to the common frontier.

After analyzing the technology of the cost frontier by looking at its parameters and the economies of scale of a select group of large banks, we check the convergence in models for λ (table 7.3), efficiency scores (table 7.4) and σ^2 (table 7.5). Again, the near perfect superposition of the endpoints should be observed (columns M1 and $S = 1$, respectively columns $S = 10^7$ and M2).

Hrvatska Postanska Bank

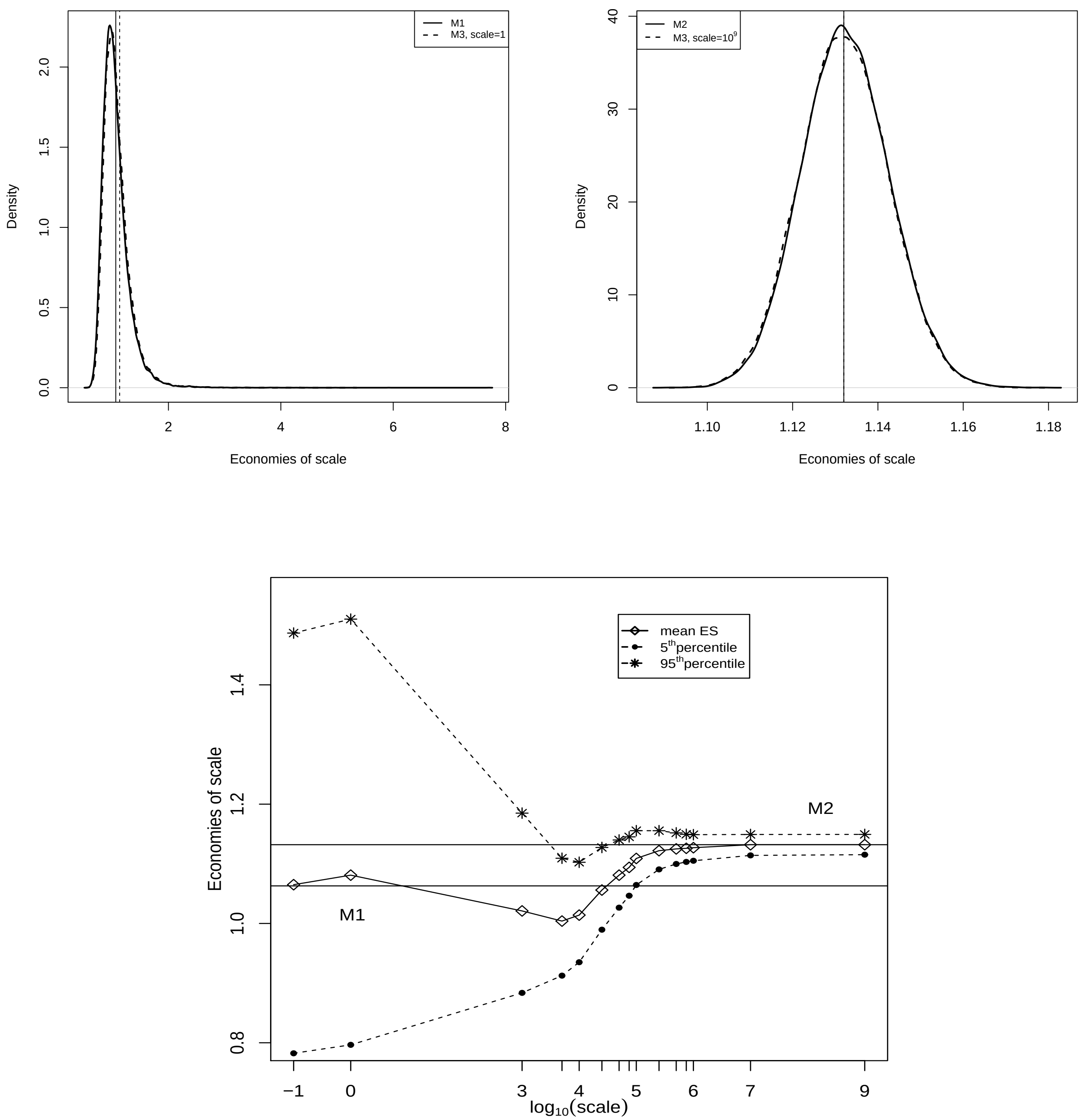

Figure 7.15: Croatia - Model Convergence, Economies of Scale, Large Bank.

Skandinaviska Enskilda Banken

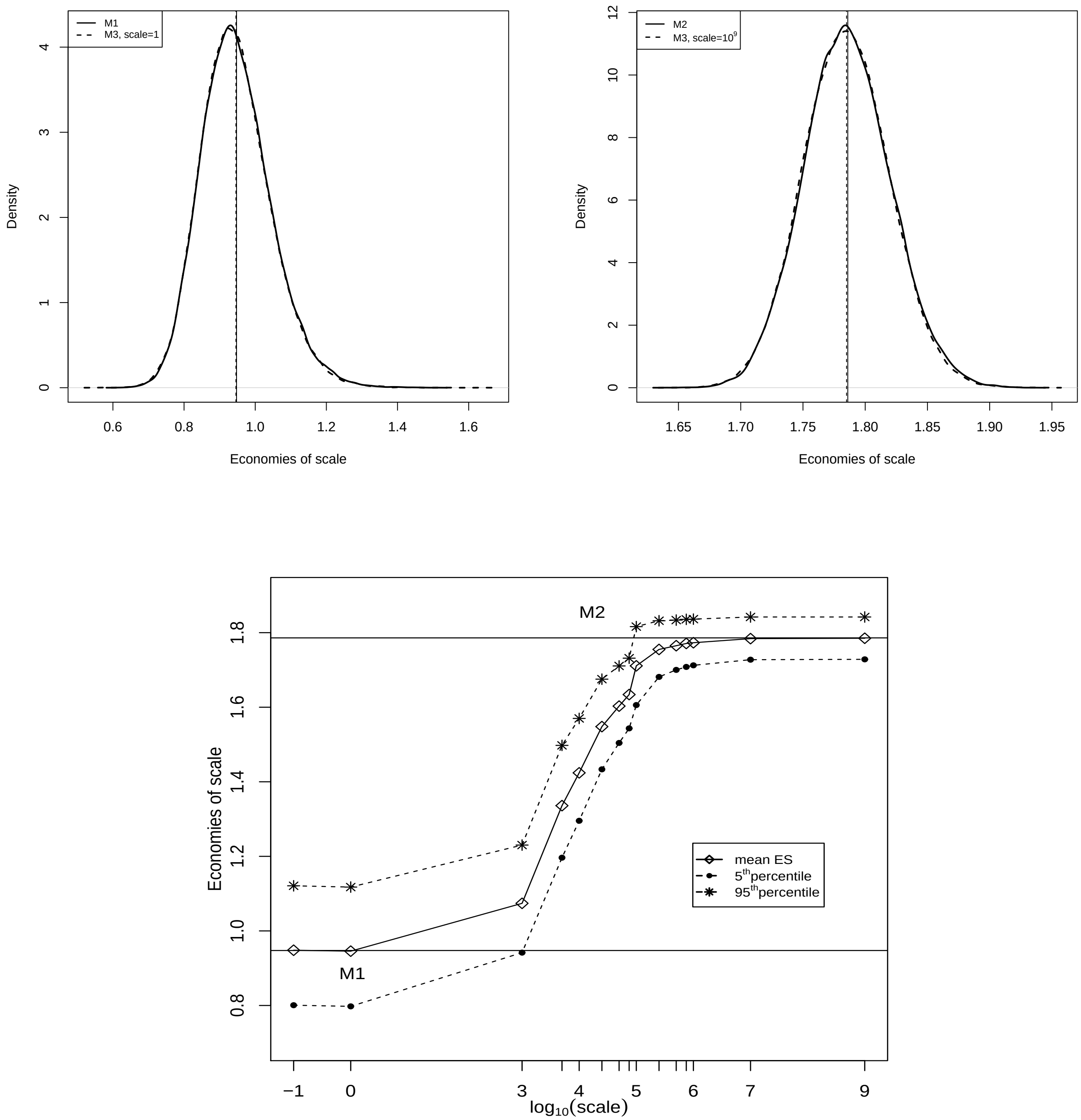

Figure 7.16: Denmark - Model Convergence, Economies of Scale, Large Bank.

Banque Populaire des Alpes

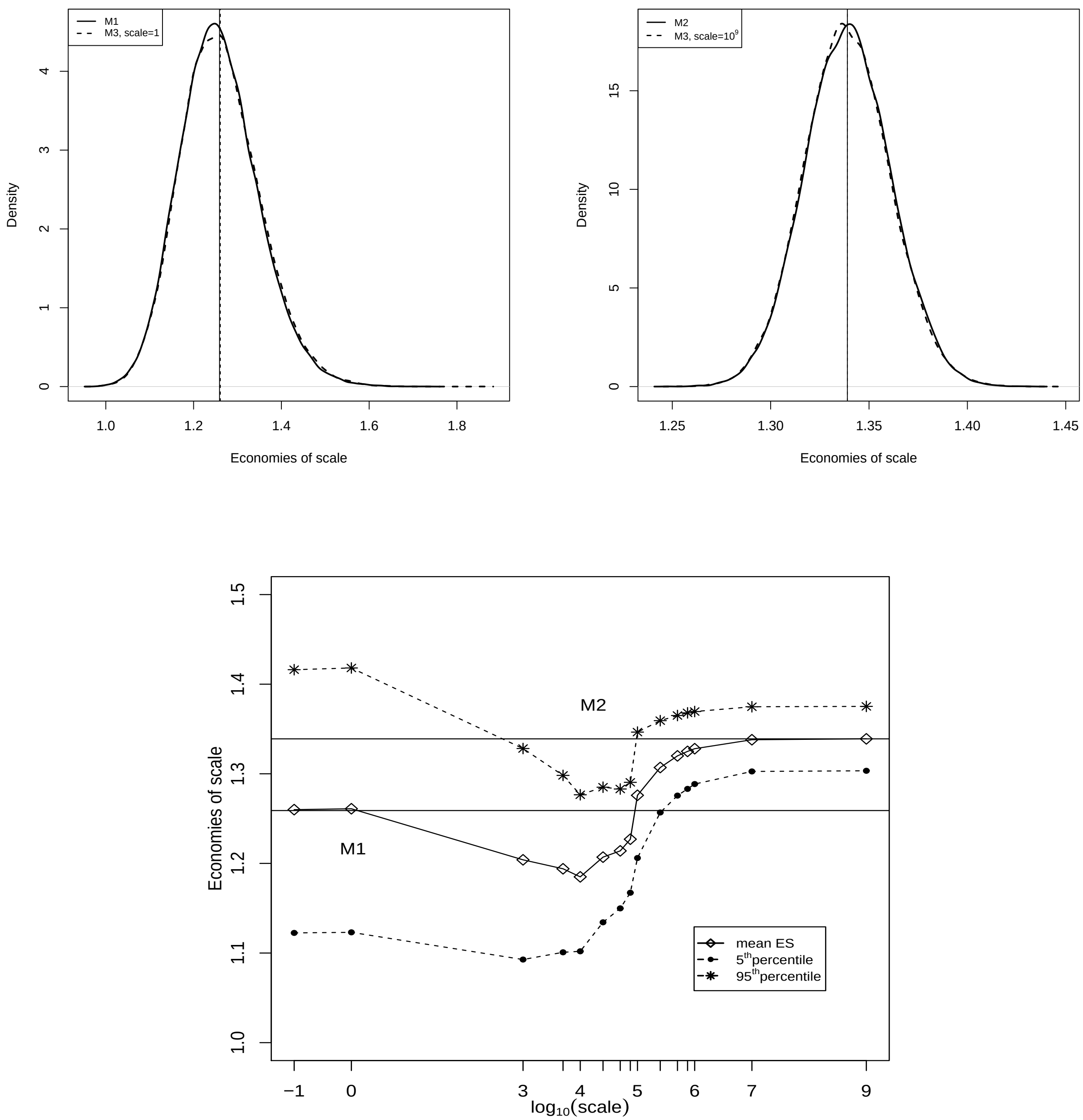

Figure 7.17: France - Model Convergence, Economies of Scale, Large Bank.

Thüringer Aufbaubank

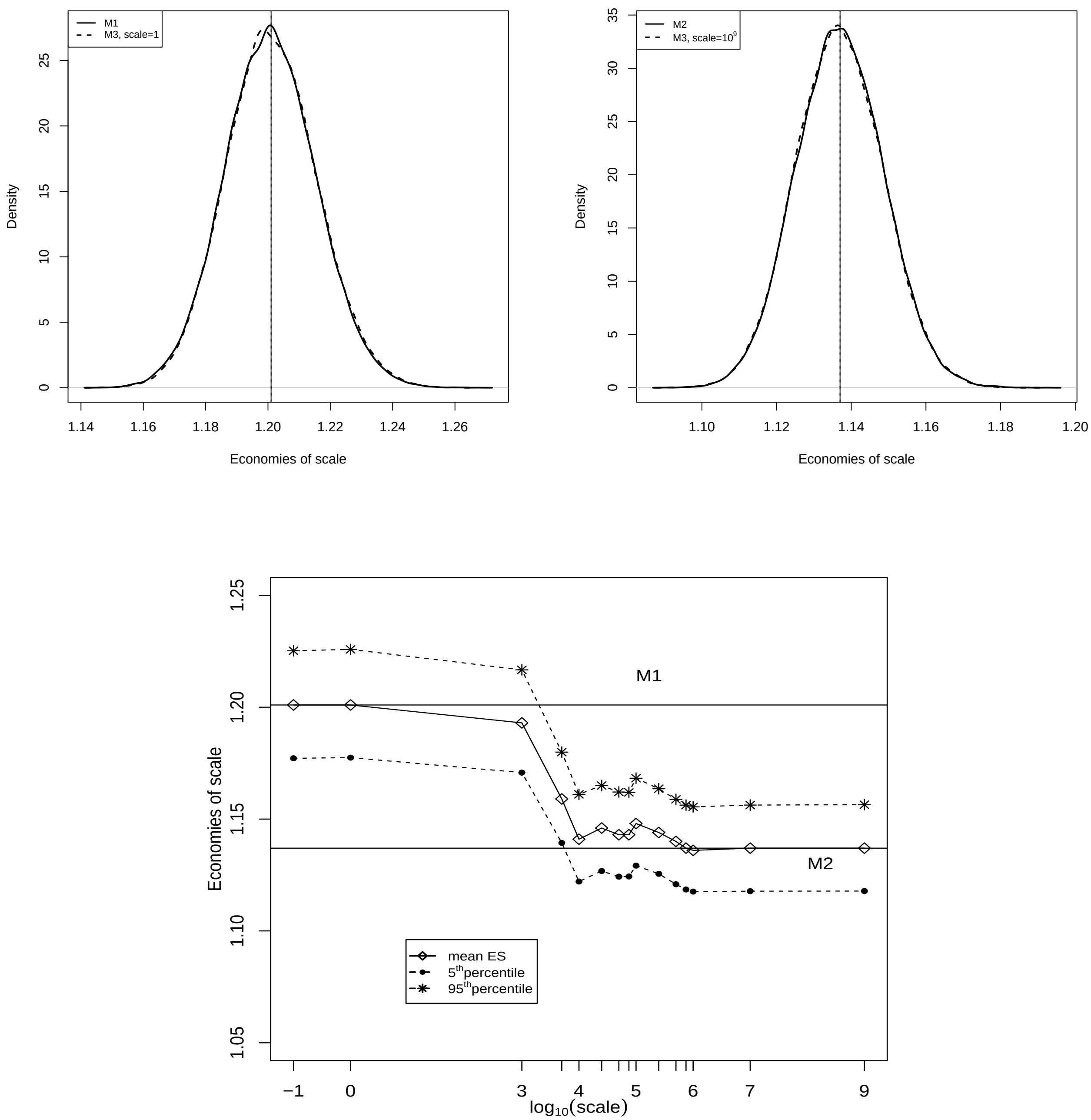

Figure 7.18: Germany - Model Convergence, Economies of Scale, Large Bank.

Banca Monte Parma SpA

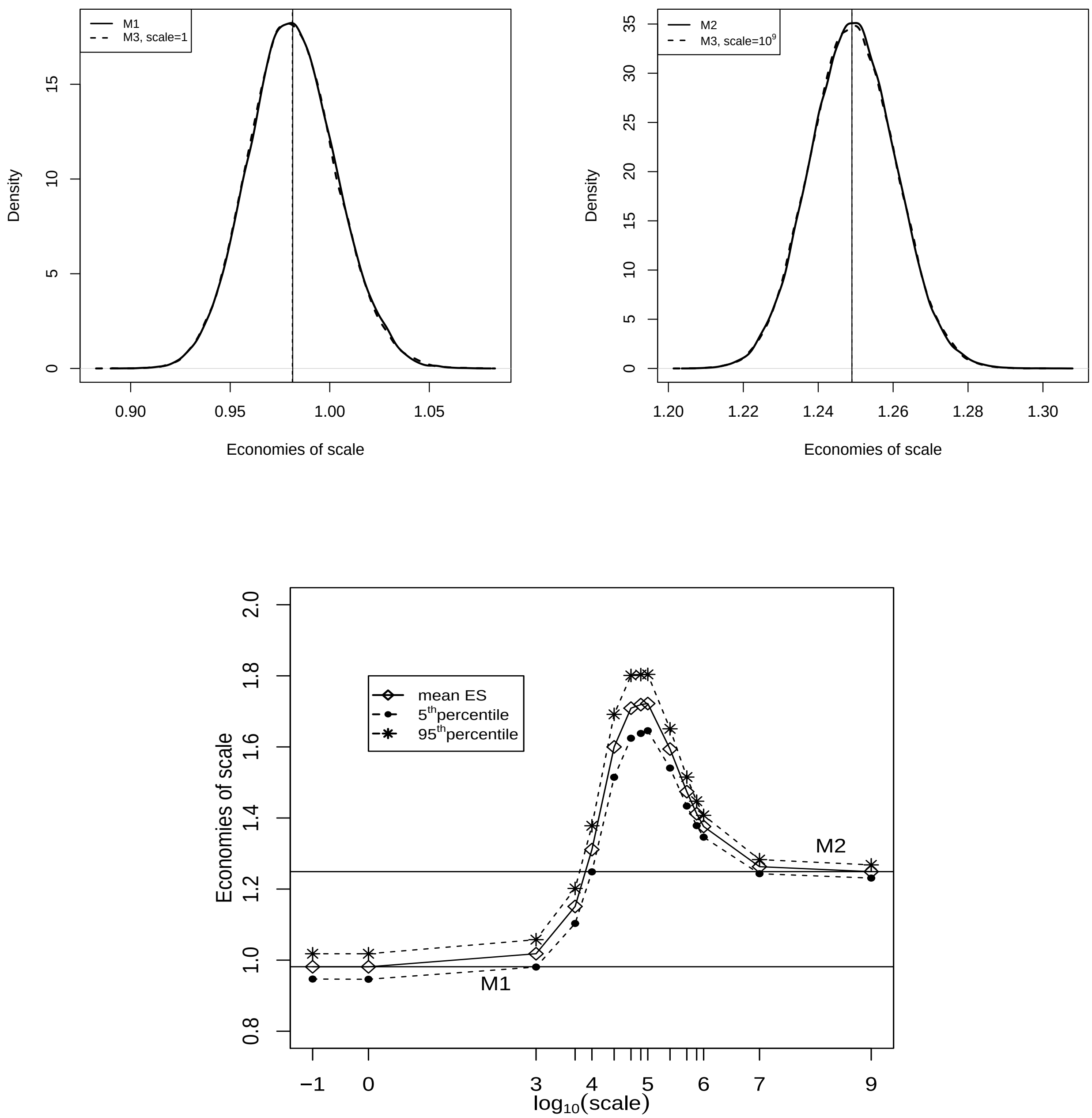

Figure 7.19: Italy - Model Convergence, Economies of Scale, Large Bank.

Staalbankiers NV

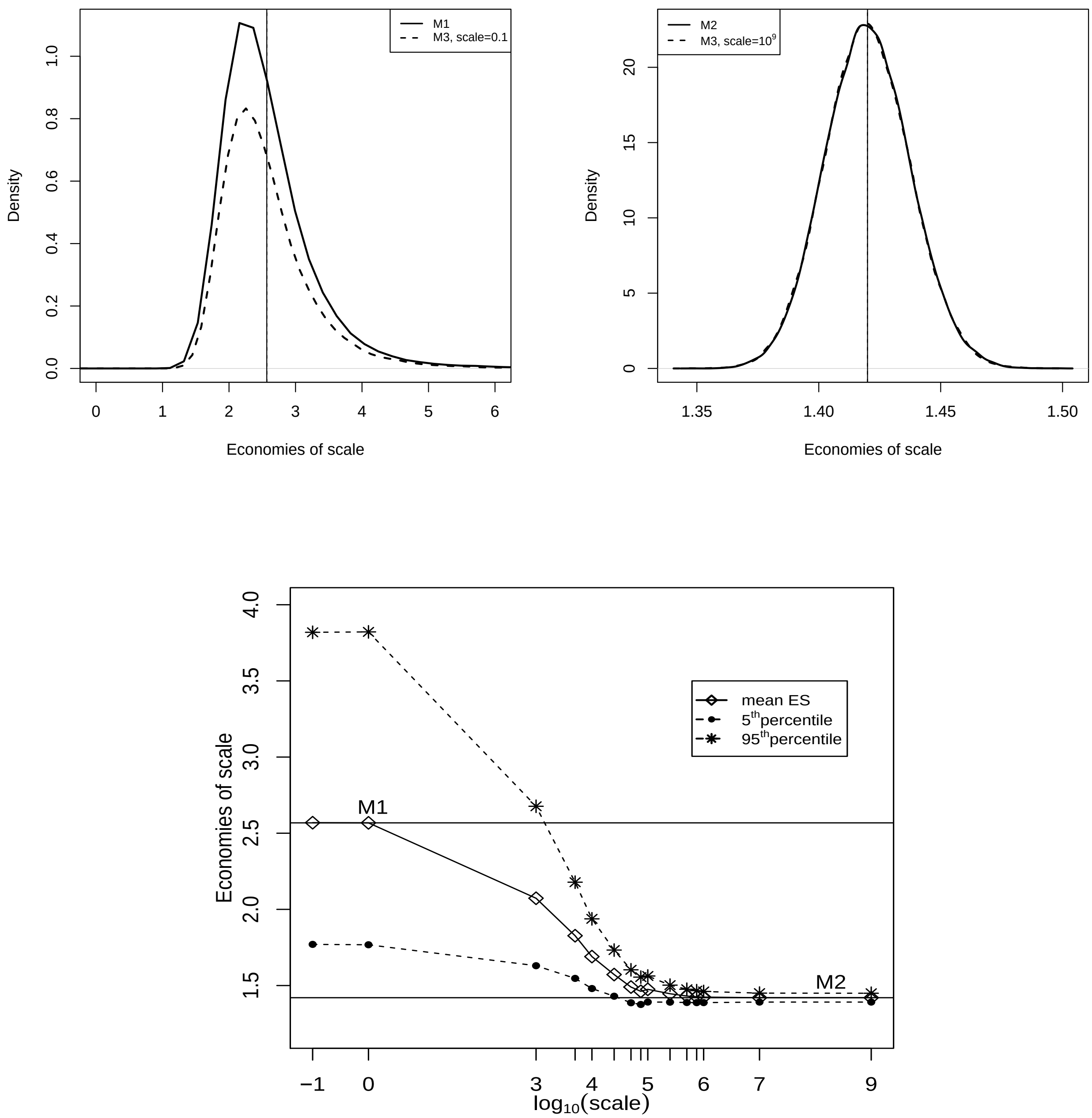

Figure 7.20: Netherlands - Model Convergence, Economies of Scale, Large Bank.

Bank BPH SA

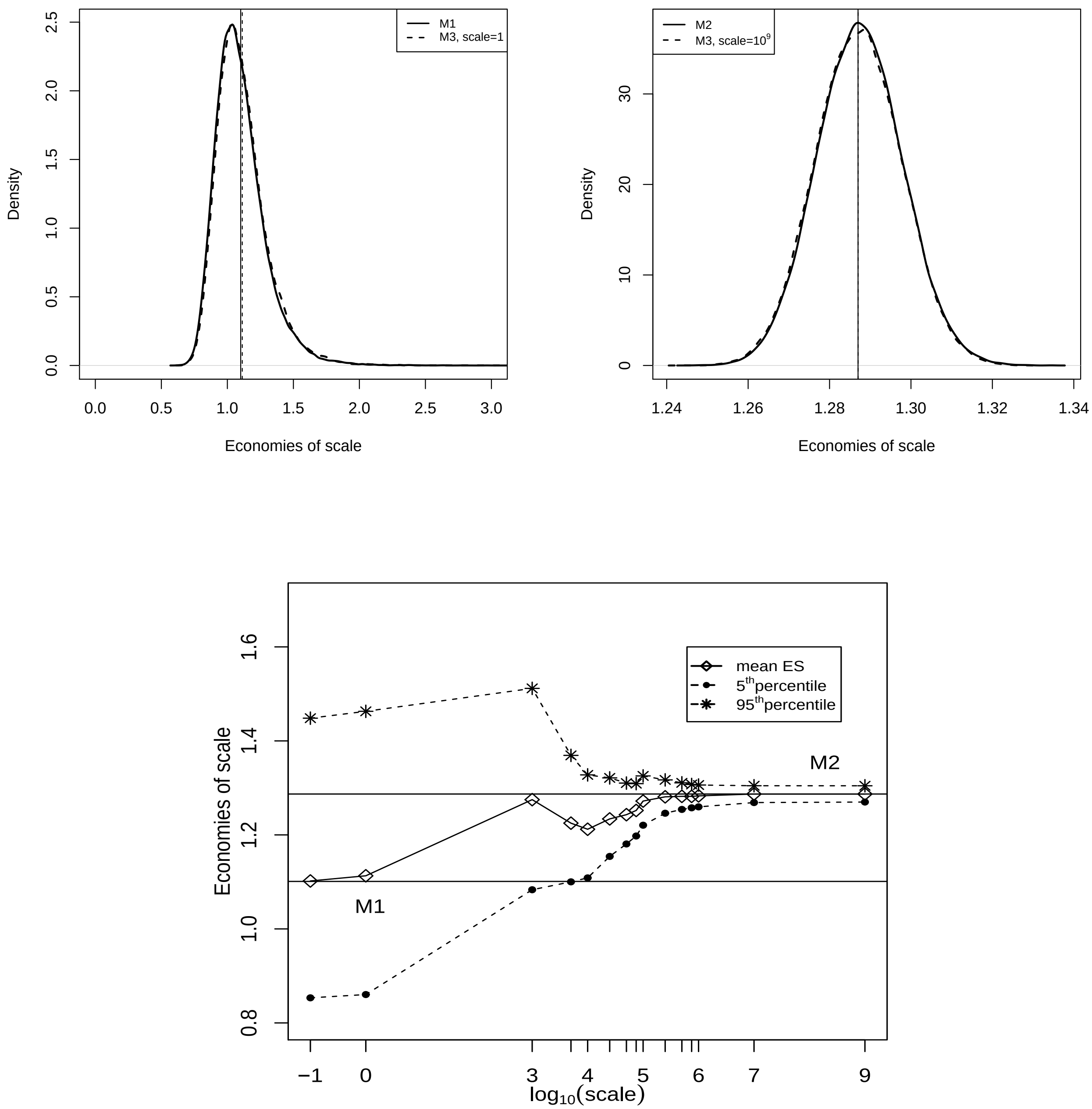

Figure 7.21: Poland - Model Convergence, Economies of Scale, Large Bank.

Banca Romaneasca

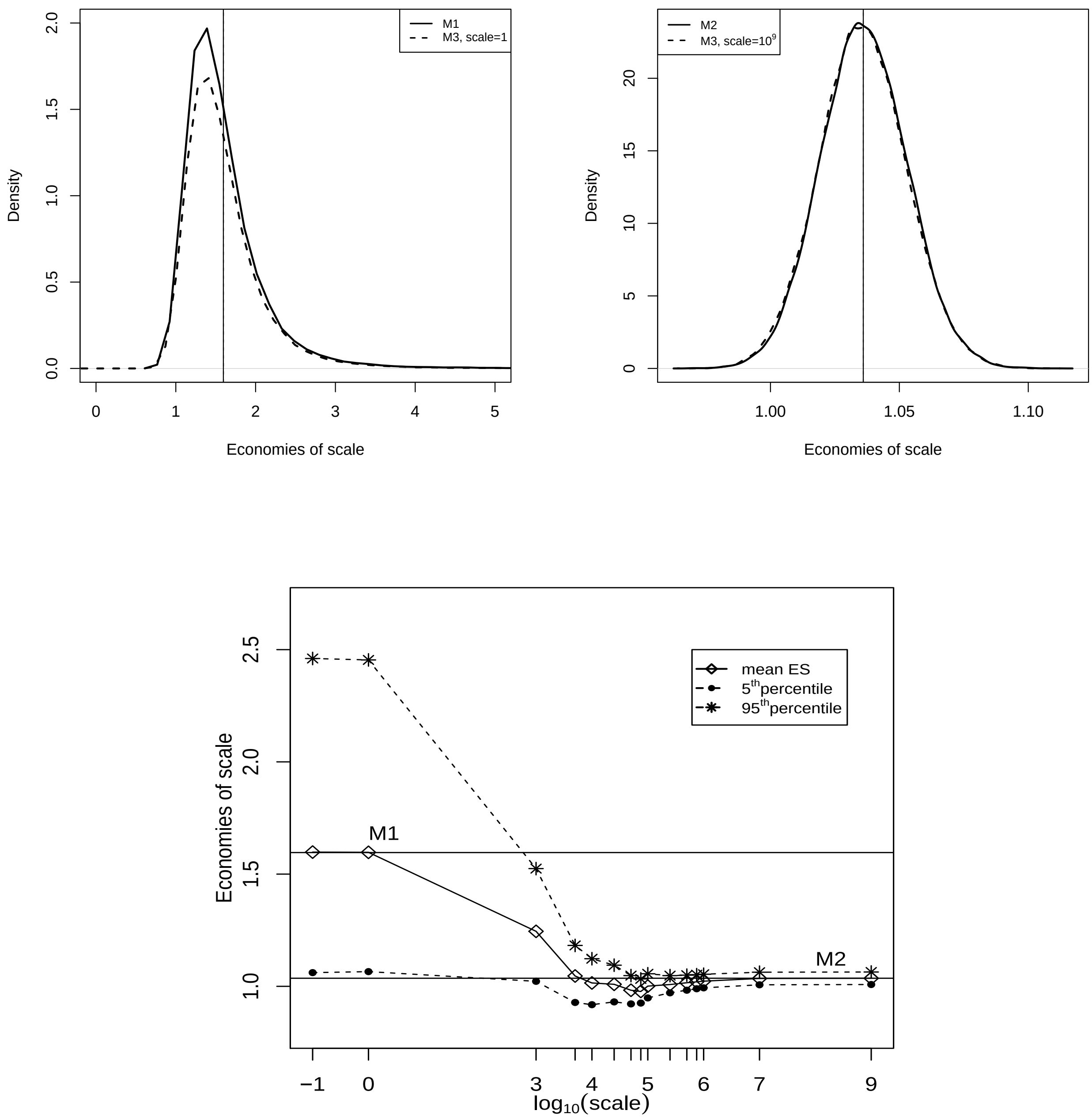

Figure 7.22: Romania - Model Convergence, Economies of Scale, Large Bank.

AIK Banka ad Nis

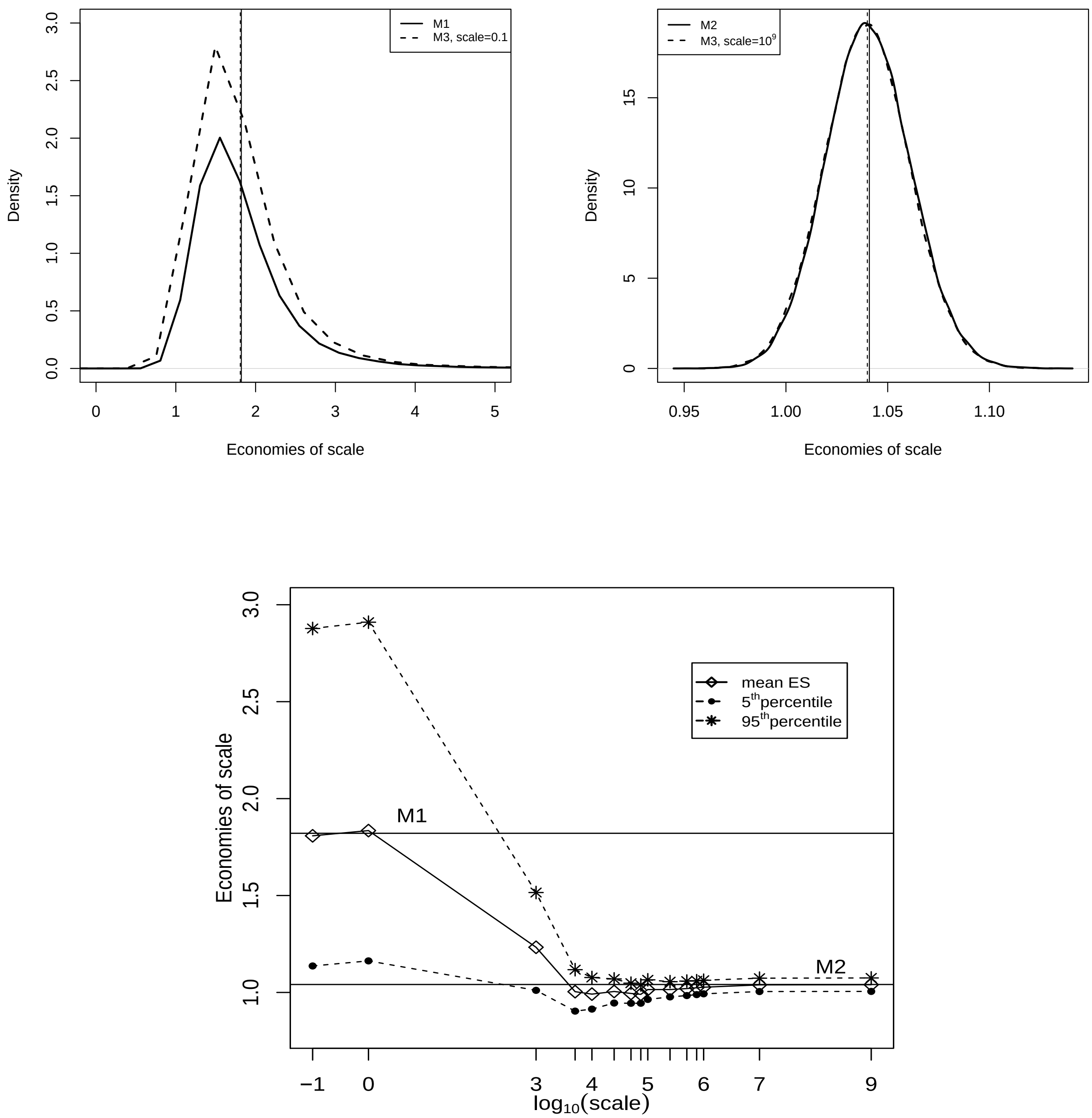

Figure 7.23: Serbia - Model Convergence, Economies of Scale, Large Bank.

Gorenjska Banka dd Kranj

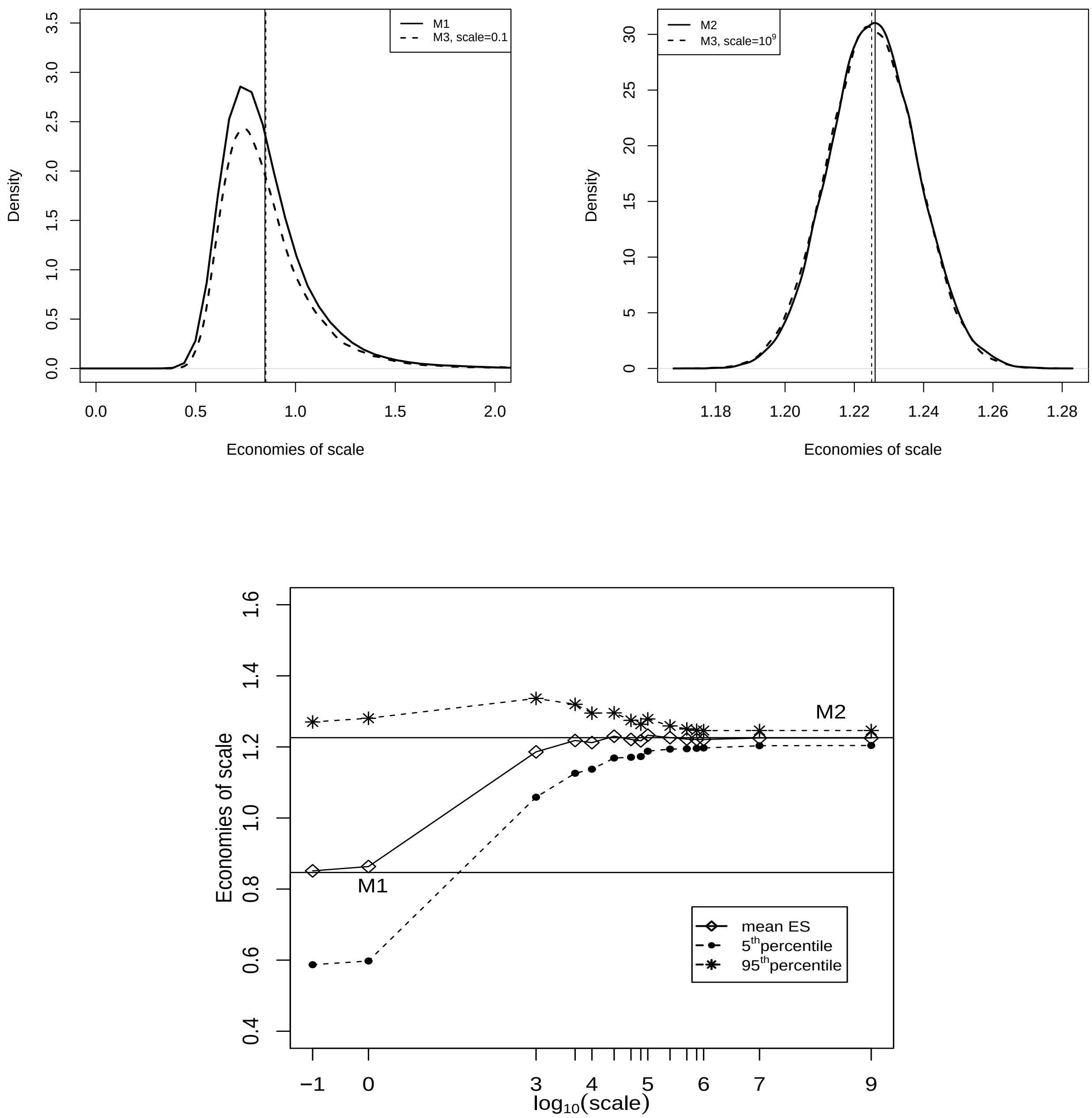

Figure 7.24: Slovenia - Model Convergence, Economies of Scale, Large Bank.

Färs & Frosta Sparbank AB

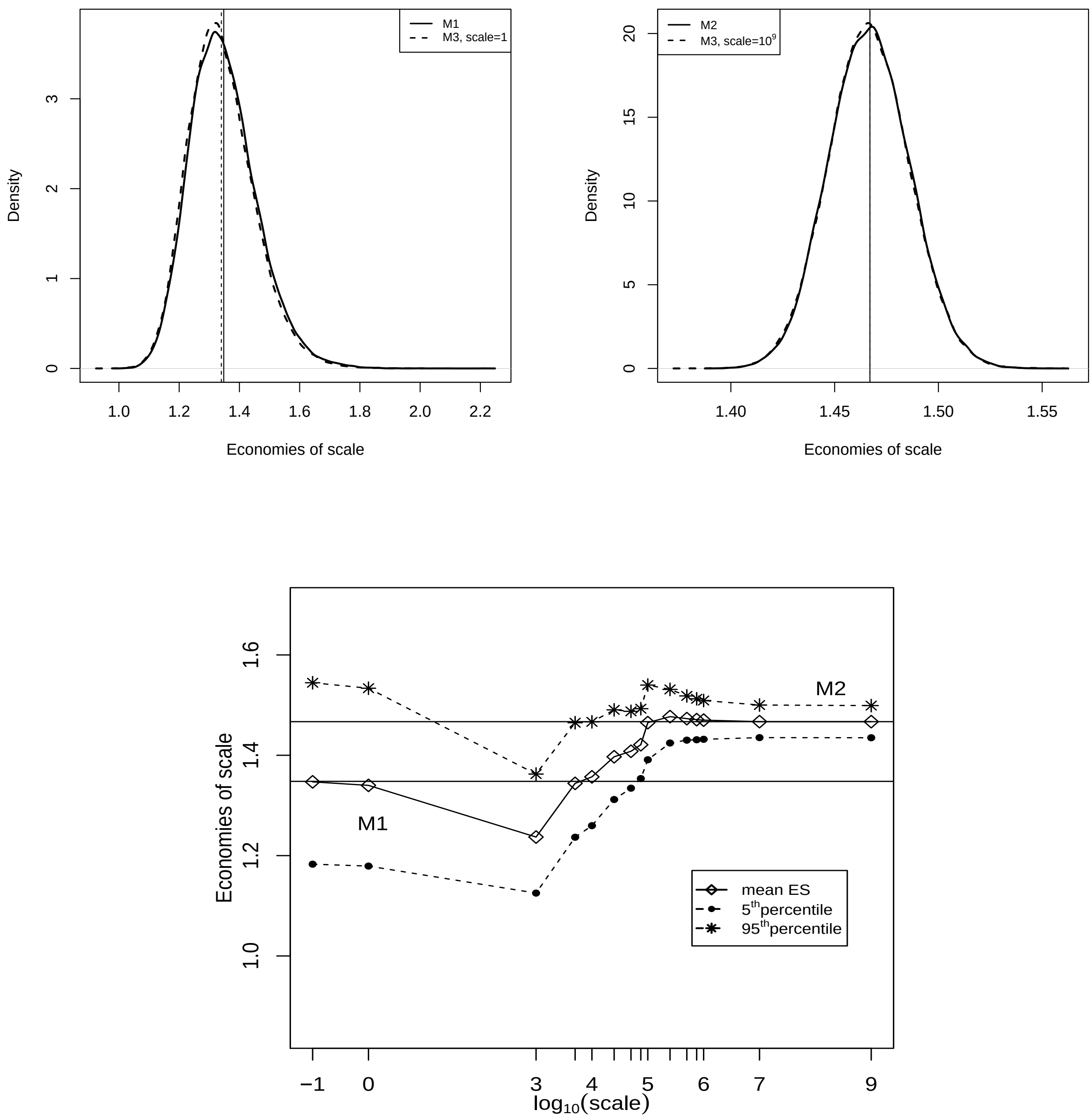

Figure 7.25: Sweden - Model Convergence, Economies of Scale, Large Bank.

ABN Amro Bank (Schweiz) AG

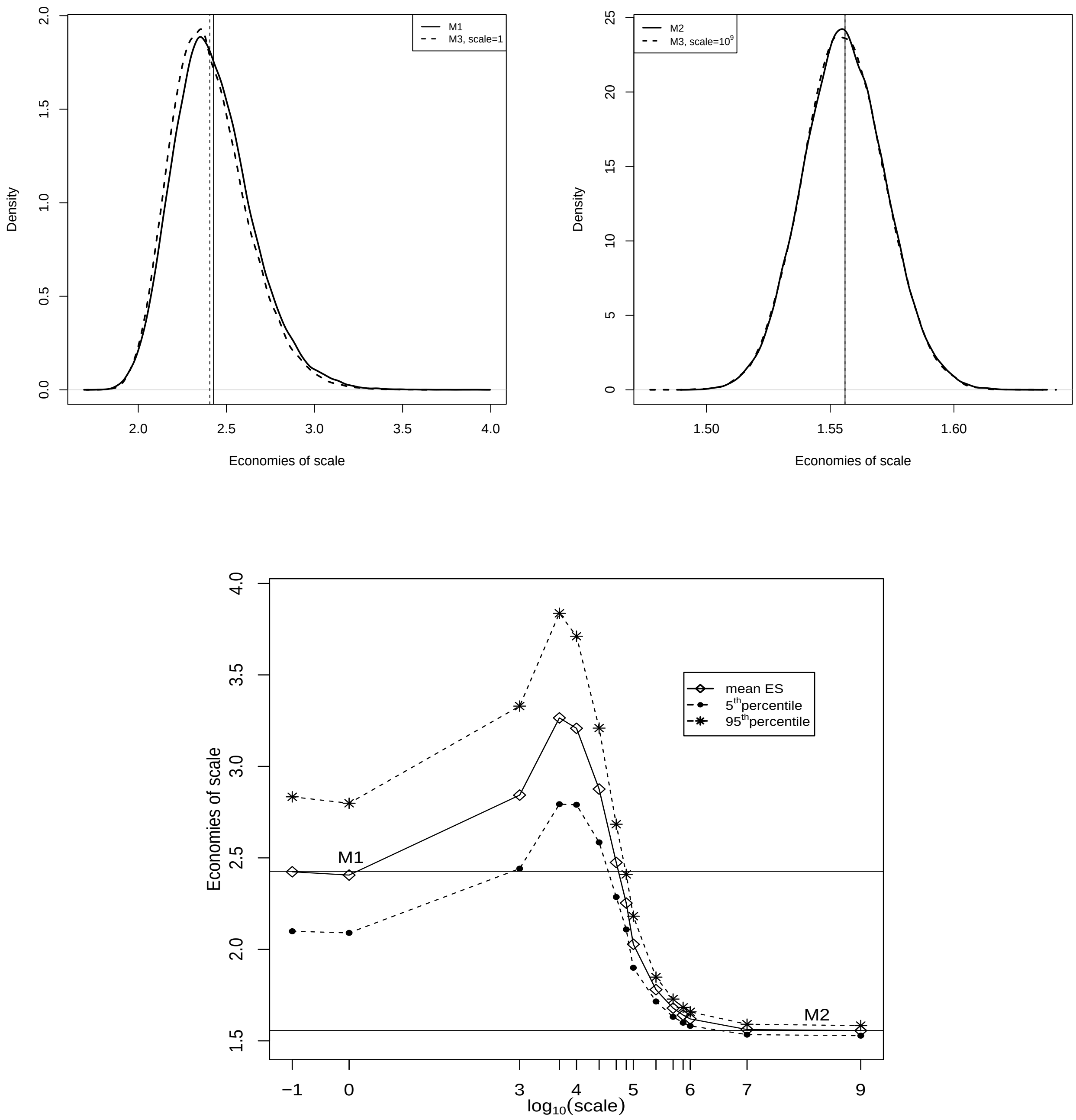

Figure 7.26: Switzerland - Model Convergence, Economies of Scale, Large Bank.

Anadolubank AS

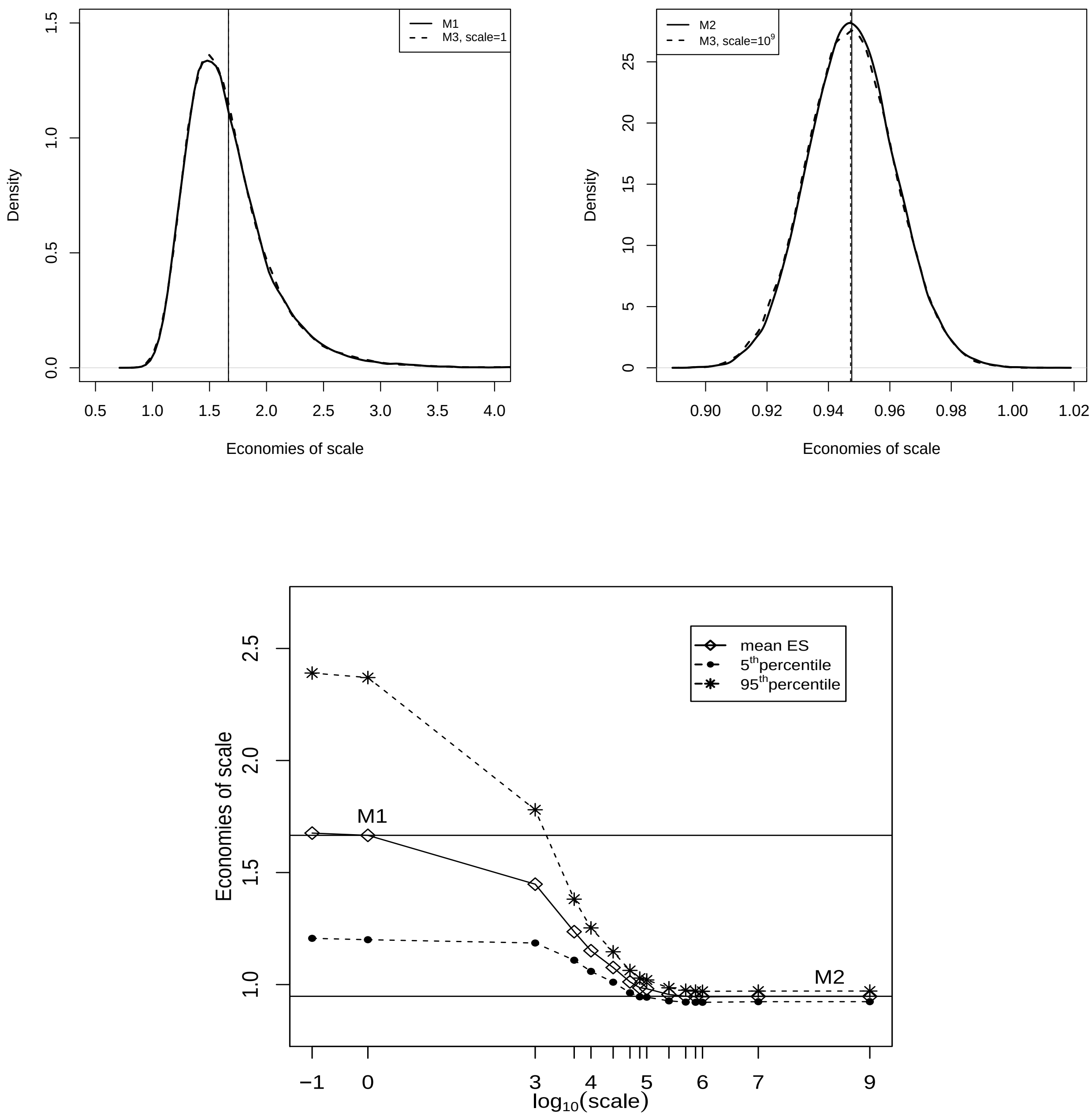

Figure 7.27: Turkey - Model Convergence, Economies of Scale, Large Bank.

JP Morgan International Bank Ltd

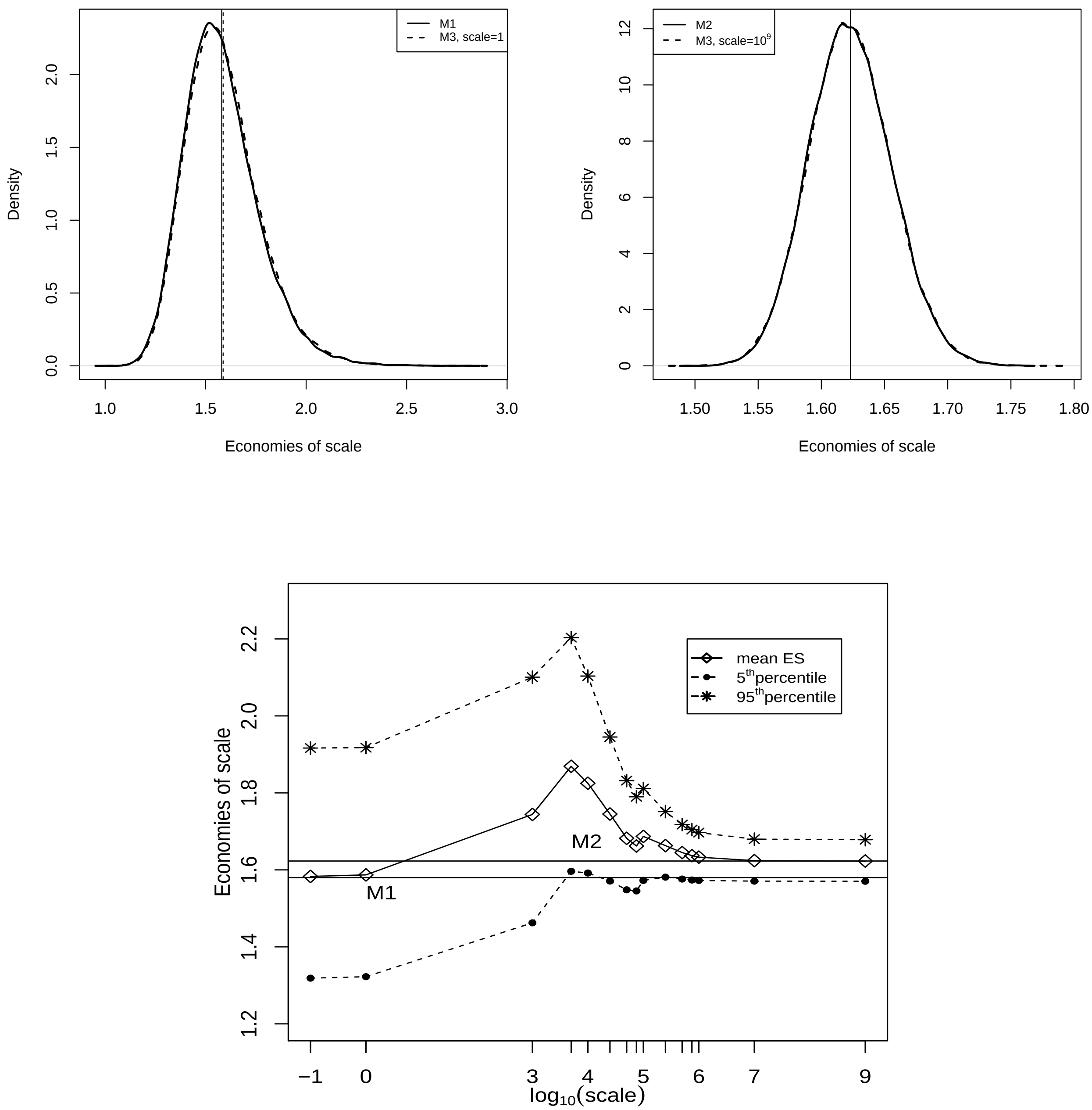

Figure 7.28: United Kingdom - Model Convergence, Economies of Scale, Large Bank.

As noted previously in chapter 6, two of the countries for which we observe very small changes for both λ (table 7.3) and the efficiency score (table 7.4) are Turkey and Germany. These are also countries that exhibit an indirect convergence between models M1 and M2. A small range for variation could very well explain such an evolution. For all the other countries, the convergence is direct.

The most dramatic increase in efficiency we notice in the case of Switzerland (from 59.86 percent to 98.47 percent) and it takes a strong prior (greater than 10^4) to see a significant increase in the posterior mean for the efficiency score, suggesting a sluggish convergence process. Using data over the period 1993-2004, Bos and Schmiedel (2007) estimate efficiency scores for both profit and cost models (with a 3-input, 3-output translog specification) using a single country, pooled and meta-frontiers (based on commercial banks data from 15 European countries). For the pooled estimates they rely on a fixed effects frontier (Greene, 2005) with country-specific fixed effects. They find higher efficiency results for Switzerland against the single (86 percent) and meta-frontier (85.4 percent) than against the pooled frontier (77 percent). Nevertheless, in a subsequent study (Bos, 2008), when using a different data set (which includes commercial, cooperative and savings banks and spans the time period 1996-2005), estimated the mean efficiency score for Switzerland's single cost frontier is 53 percent.

In conclusion, other studies also find Swiss banks to have low mean efficiency scores relative to their own country frontier, while performing better against a common "European frontier".

Another noticeable increase in efficiency as we move from single frontier to common frontier happens for France. Due to the more recent datasets that they are using, we continue to cite cost efficiency results from Bos and Schmiedel (2007) and (Bos, 2008) or Brissimis, Delis and Tsionas (2010).

Table 7.3: λ - Posterior Means, Standard Deviation, and 90% H.D.R.*

Parameters	$M_1^\lozenge$	$S^\dagger = 1$	$S = 10^3$	$S = 10^4$	$S = 10^5$	$S = 10^7$	M_2
λ_{HR}	0.1090	0.1076	0.1348	0.2756	0.4962	0.5641	0.5641
Post. S.D.	(0.0499)	(0.0514)	(0.0532)	(0.0506)	(0.0580)	(0.0620)	(0.0620)
$[H.D.R.]$	[0.038, 0.199]	[0.037, 0.200]	[0.052, 0.226]	[0.196, 0.363]	[0.406, 0.595]	[0.467, 0.671]	[0.467, 0.671]
λ_{DK}	0.1899	0.1904	0.1532	0.0568	0.0339	0.0310	0.0319
Post. S.D.	(0.0359)	(0.0368)	(0.0509)	(0.0223)	(0.0112)	(0.0100)	(0.0104)
$[H.D.R.]$	[0.133, 0.249]	[0.129, 0.249]	[0.056, 0.229]	[0.027, 0.099]	[0.019, 0.055]	[0.018, 0.049]	[0.018, 0.051]
λ_{FR}	0.4078	0.4075	0.0568	0.0566	0.0357	0.0390	0.0395
Post. S.D.	(0.0333)	(0.0326)	(0.0256)	(0.0285)	(0.0123)	(0.0131)	(0.0132)
$[H.D.R.]$	[0.353, 0.463]	[0.355, 0.462]	[0.026, 0.105]	[0.025, 0.113]	[0.020, 0.059]	[0.021, 0.063]	[0.021, 0.064]
λ_{DE}	0.1601	0.1600	0.1581	0.1598	0.1554	0.1744	0.1749
Post. S.D.	(0.0040)	(0.0039)	(0.0039)	(0.0037)	(0.0041)	(0.0038)	(0.0038)
$[H.D.R.]$	[0.154, 0.167]	[0.154, 0.166]	[0.152, 0.165]	[0.154, 0.166]	[0.149, 0.162]	[0.168, 0.181]	[0.169, 0.181]
λ_{IT}	0.2168	0.2166	0.2111	0.1761	0.0136	0.0081	0.0080
Post. S.D.	(0.0097)	(0.0095)	(0.0096)	(0.0113)	(0.0031)	(0.0014)	(0.0014)
$[H.D.R.]$	[0.201, 0.233]	[0.201, 0.232]	[0.196, 0.227]	[0.158, 0.195]	[0.009, 0.019]	[0.006, 0.011]	[0.006, 0.012]

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Parameters	$M_1^{\Diamond}$	$S^{\dagger} = 1$	$S = 10^3$	$S = 10^4$	$S = 10^5$	$S = 10^7$	M_2
λ_{NL}	0.2002	0.2093	0.1909	0.0850	0.0484	0.0507	0.0508
Post. S.D.	(0.1408)	(0.1388)	(0.1061)	(0.0471)	(0.0200)	(0.0209)	(0.0222)
[$H.D.R.$]	[0.042, 0.487]	[0.045, 0.485]	[0.047, 0.380]	[0.030, 0.178]	[0.023, 0.086]	[0.024, 0.090]	[0.023, 0.093]
λ_{PL}	0.0916	0.0921	0.1189	0.1488	0.1650	0.2252	0.2278
Post. S.D.	(0.0469)	(0.0465)	(0.0581)	(0.0618)	(0.0570)	(0.0632)	(0.0629)
[$H.D.R.$]	[0.034, 0.182]	[0.034, 0.181]	[0.042, 0.229]	[0.057, 0.259]	[0.077, 0.264]	[0.123, 0.331]	[0.125, 0.334]
λ_{RO}	0.1598	0.1626	0.3339	0.5568	0.8748	0.9454	0.9437
Post. S.D.	(0.0799)	(0.0800)	(0.0784)	(0.0858)	(0.1082)	(0.1143)	(0.1143)
[$H.D.R.$]	[0.046, 0.301]	[0.044, 0.301]	[0.210, 0.465]	[0.423, 0.704]	[0.707, 1.062]	[0.768, 1.143]	[0.766, 1.141]
λ_{RS}	0.5139	0.5254	0.7532	1.1440	1.3720	1.4240	1.4210
Post. S.D.	(0.1223)	(0.1186)	(0.1127)	(0.1629)	(0.1863)	(0.1929)	(0.1916)
[$H.D.R.$]	[0.310, 0.696]	[0.339, 0.702]	[0.584, 0.952]	[0.897, 1.430]	[1.087, 1.698]	[1.129, 1.758]	[1.125, 1.755]
λ_{SI}	0.0851	0.0885	0.0732	0.0581	0.0450	0.0443	0.0445
Post. S.D.	(0.0426)	(0.0429)	(0.0349)	(0.0254)	(0.0179)	(0.0168)	(0.0171)
[$H.D.R.$]	[0.032, 0.167]	[0.034, 0.170]	[0.029, 0.140]	[0.026, 0.107]	[0.022, 0.079]	[0.022, 0.076]	[0.022, 0.077]
λ_{SE}	0.1408	0.1377	0.0780	0.0567	0.0292	0.0282	0.0286
Post. S.D.	(0.0459)	(0.0504)	(0.0358)	(0.0247)	(0.0093)	(0.0085)	(0.0087)
[$H.D.R.$]	[0.062, 0.213]	[0.049, 0.216]	[0.031, 0.146]	[0.025, 0.105]	[0.017, 0.047]	[0.016, 0.044]	[0.016, 0.045]

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Parameters	$M_1{}^{\Diamond}$	$S^{\dagger}=1$	$S=10^3$	$S=10^4$	$S=10^5$	$S=10^7$	M_2
λ_{CH}	0.5112	0.5138	0.4748	0.4024	0.0776	0.0154	0.0152
Post. S.D.	(0.0291)	(0.0284)	(0.0277)	(0.0278)	(0.0870)	(0.0035)	(0.0036)
[$H.D.R.$]	[0.465, 0.561]	[0.467, 0.560]	[0.430, 0.521]	[0.358, 0.449]	[0.016, 0.249]	[0.010, 0.022]	[0.010, 0.022]
λ_{TR}	0.1863	0.1815	0.2606	0.2899	0.2095	0.2227	0.2221
Post. S.D.	(0.0752)	(0.0779)	(0.0652)	(0.0489)	(0.0509)	(0.0462)	(0.0458)
[$H.D.R.$]	[0.058, 0.305]	[0.053, 0.306]	[0.154, 0.369]	[0.214, 0.373]	[0.123, 0.291]	[0.149, 0.298]	[0.149, 0.297]
λ_{UK}	0.1653	0.1464	0.1522	0.1354	0.0486	0.0464	0.0502
Post. S.D.	(0.1011)	(0.0895)	(0.0771)	(0.0588)	(0.0200)	(0.0181)	(0.0196)
[$H.D.R.$]	[0.040, 0.359]	[0.041, 0.325]	[0.050, 0.296]	[0.047, 0.240]	[0.023, 0.087]	[0.022, 0.080]	[0.025, 0.087]

Notes:
$*$ Highest Density Region.
$\Diamond$ Based on national frontiers (M1).
$\dagger S^i$ stands for a scale factor of order 10^i.
Posterior moments are computed based on 50,000 points generated from the Gibbs sampling algorithm. The end points of the 90% confidence region are the 5^{th} and the 95^{th} percentiles of the posterior marginal densities.

Whether they use the pooled (74.5 percent), single (72.5 percent) or the meta-frontier approach (72.2 percent), Bos and Schmiedel (2007) find the cost efficiency values of the French banks to be within the 70-75 percent range. Computed against the own country's frontier, (Bos, 2008) finds the average cost efficiency of the French banks to be 82.7 percent. Using a multitude of techniques [10], and commercial banks data for 1996-2003, Brissimis, Delis and Tsionas (2010) estimate both the technical and allocative efficiency for the banking systems from 13 European countries. For comparison, they find the average technical efficiency of the French banks to be 89.48 percent.

Italy comes up in model M2 with a surprisingly high mean efficiency score (99.2 percent). Bos and Schmiedel (2007) found the opposite result as the efficiency improves for the Italian banks when computer against their own frontier (81.8 percent) rather than the pooled frontier (76.1 percent).

In general, we find that most of the Western European countries fare better under the common frontier assumption (with the exception of Germany for which the efficiency drops by a negligible 1 percentage point) and this is what we would have expected. Therefore, for Germany, Italy, Denmark, Sweden, France, Italy, Netherlands or United Kingdom, the common frontier assumption paints a similar picture to the one we found when looking at the single frontier results. These are cost efficient banking systems and it matters less if the efficiency score is 85 percent or 90 percent. Switzerland's case is definitely more intriguing.

As we move from weak to strong prior and thus from M1 (single frontier) to M2 (common frontier), the other interesting evolution that needs to be mentioned is the spectacular drop in efficiency registered by most of the Easter block countries: Serbia (from 60.28 percent to 24.59 percent), Romania (from 85.5 percent to 39.17 percent), Croatia (from 89.79 percent to 57 percent), Poland (from 91.35 percent to 79.78 percent).

[10] maximum likelihood, Nelder and Mear simplex maximization technique, Metropolis-Hastings and MCMC

Table 7.4: Efficiency Score - Posterior Means, Standard Deviation,and 90% H.D.R.*

Parameters	M_1 ◊	$S^\dagger = 1$	$S = 10^3$	$S = 10^4$	$S = 10^5$	$S = 10^7$	M_2
r_{HR}	0.8979	0.8991	0.8751	0.7601	0.6099	0.5700	0.5700
Post. S.D.	(0.0442)	(0.0456)	(0.0462)	(0.0382)	(0.0351)	(0.0350)	0.0351
[$H.D.R.$]	[0.820, 0.962]	[0.819, 0.964]	[0.798, 0.949]	[0.696, 0.822]	[0.551, 0.666]	[0.511, 0.627]	[0.511, 0.627]
r_{DK}	0.8276	0.8272	0.8591	0.9450	0.9667	0.9695	0.9686
Post. S.D.	(0.0297)	(0.0305)	(0.0441)	(0.0209)	(0.0108)	(0.0096)	0.0100
[$H.D.R.$]	[0.780, 0.876]	[0.779, 0.879]	[0.795, 0.945]	[0.906, 0.974]	[0.947, 0.982]	[0.952, 0.983]	[0.950, 0.983]
r_{FR}	0.6655	0.6656	0.9451	0.9454	0.9650	0.9618	0.9613
Post. S.D.	(0.0222)	(0.0217)	(0.0238)	(0.0263)	(0.0118)	(0.0125)	0.0127
[$H.D.R.$]	[0.629, 0.702]	[0.630, 0.701]	[0.900, 0.975]	[0.894, 0.977]	[0.943, 0.981]	[0.939, 0.980]	[0.938, 0.979]
r_{DE}	0.8521	0.8521	0.8538	0.8523	0.8561	0.8400	0.8395
Post. S.D.	(0.0034)	(0.0033)	(0.0033)	(0.0032)	(0.0035)	(0.0032)	0.0032
[$H.D.R.$]	[0.847, 0.858]	[0.847, 0.858]	[0.848, 0.859]	[0.847, 0.857]	[0.850, 0.862]	[0.835, 0.845]	[0.834, 0.845]
r_{IT}	0.8051	0.8053	0.8097	0.8386	0.9865	0.9919	0.9920
Post. S.D.	(0.0078)	(0.0077)	(0.0078)	(0.0094)	(0.0031)	(0.0014)	0.0014
[$H.D.R.$]	[0.792, 0.818]	[0.793, 0.818]	[0.797, 0.823]	[0.823, 0.854]	[0.981, 0.991]	[0.989, 0.994]	[0.989, 0.994]

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Parameters	$M_1^\diamond$	$S^\dagger = 1$	$S = 10^3$	$S = 10^4$	$S = 10^5$	$S = 10^7$	M_2
r_{NL}	0.8263	0.8187	0.8308	0.9195	0.9530	0.9507	0.9507
Post. S.D.	(0.1086)	(0.1068)	(0.0858)	(0.0420)	(0.0188)	(0.0196)	0.0208
[$H.D.R.$]	[0.615, 0.959]	[0.616, 0.956]	[0.684, 0.955]	[0.837, 0.970]	[0.918, 0.977]	[0.914, 0.976]	[0.911, 0.977]
r_{PL}	0.9135	0.9130	0.8894	0.8634	0.8493	0.7999	0.7978
Post. S.D.	(0.0417)	(0.0414)	(0.0504)	(0.0526)	(0.0479)	(0.0504)	0.0501
[$H.D.R.$]	[0.833, 0.966]	[0.835, 0.967]	[0.796, 0.959]	[0.772, 0.944]	[0.768, 0.926]	[0.719, 0.885]	[0.716, 0.882]
r_{RO}	0.8550	0.8526	0.7183	0.5751	0.4194	0.3910	0.3917
Post. S.D.	(0.0672)	(0.0673)	(0.0563)	(0.0488)	(0.0447)	(0.0440)	0.0442
[$H.D.R.$]	[0.740, 0.955]	[0.740, 0.957]	[0.628, 0.811]	[0.494, 0.655]	[0.346, 0.493]	[0.319, 0.464]	[0.320, 0.465]
r_{RS}	0.6028	0.5956	0.4738	0.3228	0.2579	0.2453	0.2459
Post. S.D.	(0.0776)	(0.0748)	(0.0523)	(0.0512)	(0.0468)	(0.0462)	0.0461
[$H.D.R.$]	[0.499, 0.734]	[0.495, 0.713]	[0.386, 0.558]	[0.239, 0.408]	[0.183, 0.337]	[0.172, 0.324]	[0.173, 0.325]
r_{SI}	0.9193	0.9161	0.9300	0.9438	0.9561	0.9568	0.9566
Post. S.D.	(0.0383)	(0.0385)	(0.0319)	(0.0236)	(0.0170)	(0.0160)	0.0162
[$H.D.R.$]	[0.846, 0.969]	[0.843, 0.967]	[0.869, 0.971]	[0.899, 0.975]	[0.925, 0.978]	[0.927, 0.978]	[0.926, 0.978]
r_{SE}	0.8696	0.8725	0.9256	0.9452	0.9712	0.9722	0.9718
Post. S.D.	(0.0401)	(0.0441)	(0.0327)	(0.0231)	(0.0090)	(0.0083)	0.0085
[$H.D.R.$]	[0.809, 0.940]	[0.806, 0.952]	[0.864, 0.970]	[0.901, 0.976]	[0.954, 0.984]	[0.957, 0.984]	[0.956, 0.984]

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Parameters	$M_1{}^{\Diamond}$	$S^{\dagger} = 1$	$S = 10^3$	$S = 10^4$	$S = 10^5$	$S = 10^7$	M_2
r_{CH}	0.5986	0.5985	0.6222	0.6690	0.9287	0.9847	0.9849
Post. S.D.	(0.0174)	(0.0170)	(0.0172)	(0.0186)	(0.0765)	(0.0035)	0.0035
[$H.D.R.$]	[0.571, 0.628]	[0.571, 0.627]	[0.594, 0.651]	[0.639, 0.699]	[0.780, 0.984]	[0.979, 0.990]	[0.979, 0.990]
r_{TR}	0.8324	0.8366	0.7722	0.7493	0.8120	0.8012	0.8017
Post. S.D.	(0.0627)	(0.0651)	(0.0504)	(0.0364)	(0.0416)	(0.0372)	0.0368
[$H.D.R.$]	[0.737, 0.944]	[0.737, 0.948]	[0.692, 0.857]	[0.689, 0.808]	[0.748, 0.884]	[0.742, 0.862]	[0.743, 0.862]
r_{UK}	0.8519	0.8671	0.8613	0.8749	0.9527	0.9548	0.9512
Post. S.D.	(0.0829)	(0.0738)	(0.0648)	(0.0509)	(0.0189)	(0.0171)	0.0184
[$H.D.R.$]	[0.698, 0.961]	[0.723, 0.960]	[0.744, 0.952]	[0.787, 0.954]	[0.917, 0.977]	[0.923, 0.978]	[0.916, 0.976]

Notes:
$*$ Highest Density Region.
$\Diamond$ Based on national frontiers (M1).
$\dagger S^i$ stands for a scale factor of order 10^i.
Posterior moments are computed based on 50,000 points generated from the Gibbs sampling algorithm. The end points of the 90% confidence region are the 5^{th} and the 95^{th} percentiles of the posterior marginal densities.

Slovenia is the only former communist country for which the mean efficiency score increases (negligible though) as we move from M1 to M2 (from 91.93 percent to 95.66 percent).

The studies that take a look at the banking systems of former communist countries from the Eastern European block are few and far in between and this is one reason why we introduced them in our study. Fries and Taci (2005) looked at the cost efficiency of 15 Eastern European countries using data from the 1994-2001 time period by assuming a common frontier and using country-level factors. They find slightly higher cost efficiency when accounting for differences in the economic environment (use of country-level factors. The reported efficiency levels are 72 percent for Croatia, 74 percent for Poland, 55 percent for Romania and 78 percent for Slovenia.

Staikouras at. al. (2008) use 1998-2003 bank data from 6 South Eastern European countries and for Romania they report an inefficiency level of 35.9 percent and for Croatia, 37.1 percent. These estimates are obtained based on a common frontier with country specific variables.

Using a single country frontier approach, Bos (2008) finds the following average efficiency levels: Croatia - 79.3 percent, Poland - 80.8 percent, and Slovenia - 84.3 percent.

The low efficiency levels for these countries are not surprising because in spite of the transition to the market system that they all went through during the 1990's, most of them still face corruption problems or maintain too much personnel (over staffing) which leads to higher labor costs in spite of the low wages.

The last tables of this chapter (table 7.5) records the convergence results for σ^2 and as mentioned before, an increase in the values of the posterior mean for σ^2 can be observed for countries like: Switzerland, Serbia, France and Netherlands.

Table 7.5: σ^2 - Posterior Means, Standard Deviation,and 90% H.D.R.*

Parameters	$M_1^{\Diamond}$	$S^{\dagger} = 1$	$S = 10^3$	$S = 10^4$	$S = 10^5$	$S = 10^7$	M_2
σ^2_{HR}	0.0832	0.0833	0.0825	0.0649	0.0537	0.0568	0.0567
Post. S.D.	(0.0157)	(0.0158)	(0.0161)	(0.0151)	(0.0197)	(0.0241)	0.0242
$[H.D.R.]$	[0.058, 0.110]	[0.058, 0.110]	[0.057, 0.110]	[0.042, 0.092]	[0.027, 0.090]	[0.024, 0.102]	[0.0243, 0.102]
σ^2_{DK}	0.0939	0.0937	0.1117	0.1579	0.1917	0.2045	0.2046
Post. S.D.	(0.0125)	(0.0128)	(0.0176)	(0.0126)	(0.0145)	(0.0153)	0.0152
$[H.D.R.]$	[0.074, 0.115]	[0.074, 0.116]	[0.085, 0.142]	[0.138, 0.179]	[0.169, 0.217]	[0.181, 0.231]	[0.181, 0.231]
σ^2_{FR}	0.0586	0.0589	0.2193	0.2587	0.2880	0.3007	0.3014
Post. S.D.	(0.0112)	(0.0109)	(0.0147)	(0.0179)	(0.0187)	(0.0189)	0.0190
$[H.D.R.]$	[0.042, 0.079]	[0.043, 0.078]	[0.196, 0.244]	[0.231, 0.289]	[0.259, 0.320]	[0.271, 0.333]	[0.272, 0.334]
σ^2_{DE}	0.0329	0.0329	0.0337	0.0343	0.0368	0.0360	0.0360
Post. S.D.	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0010)	(0.0009)	0.0009
$[H.D.R.]$	[0.031, 0.034]	[0.032, 0.034]	[0.032, 0.035]	[0.033, 0.036]	[0.035, 0.038]	[0.035, 0.038]	[0.035, 0.037]
σ^2_{IT}	0.0386	0.0387	0.0398	0.0570	0.1412	0.2535	0.2612
Post. S.D.	(0.0024)	(0.0024)	(0.0024)	(0.0040)	(0.0052)	(0.0092)	0.0095
$[H.D.R.]$	[0.035, 0.043]	[0.035, 0.043]	[0.036, 0.044]	[0.051, 0.064]	[0.133, 0.150]	[0.239, 0.269]	[0.246, 0.277]

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Parameters	$M_1^{\Diamond}$	$S^{\dagger} = 1$	$S = 10^3$	$S = 10^4$	$S = 10^5$	$S = 10^7$	M_2
σ^2_{NL}	0.3548	0.3523	0.4166	0.5183	0.6062	0.6349	0.6351
Post. S.D.	(0.0808)	(0.0802)	(0.0775)	(0.0702)	(0.0791)	(0.0796)	0.0798
[*H.D.R.*]	[0.200, 0.474]	[0.202, 0.473]	[0.291, 0.546]	[0.412, 0.641]	[0.488, 0.746]	[0.516, 0.775]	[0.516, 0.775]
σ^2_{PL}	0.1796	0.1794	0.2280	0.2382	0.2689	0.2733	0.2721
Post. S.D.	(0.0303)	(0.0301)	(0.0384)	(0.0402)	(0.0469)	(0.0511)	0.0506
[*H.D.R.*]	[0.136, 0.234]	[0.136, 0.234]	[0.172, 0.297]	[0.179, 0.320]	[0.200, 0.353]	[0.200, 0.365]	[0.199, 0.363]
σ^2_{RO}	0.1144	0.1134	0.1066	0.0941	0.1063	0.1250	0.1258
Post. S.D.	(0.0301)	(0.0296)	(0.0332)	(0.0338)	(0.0562)	(0.0680)	0.0674
[*H.D.R.*]	[0.066, 0.164]	[0.066, 0.163]	[0.059, 0.167]	[0.048, 0.157]	[0.032, 0.211]	[0.036, 0.253]	[0.037, 0.253]
σ^2_{RS}	0.0988	0.0920	0.0707	0.1874	0.2695	0.3209	0.3228
Post. S.D.	(0.0660)	(0.0614)	(0.0395)	(0.1053)	(0.1600)	(0.1775)	0.1757
[*H.D.R.*]	[0.034, 0.233]	[0.032, 0.207]	[0.026, 0.146]	[0.057, 0.385]	[0.066, 0.572]	[0.082, 0.651]	[0.085, 0.648]
σ^2_{SI}	0.0808	0.0801	0.1143	0.1248	0.1284	0.1265	0.1264
Post. S.D.	(0.0156)	(0.0156)	(0.0204)	(0.0208)	(0.0209)	(0.0206)	0.0204
[*H.D.R.*]	[0.058, 0.108]	[0.057, 0.108]	[0.085, 0.151]	[0.095, 0.162]	[0.098, 0.166]	[0.097, 0.164]	[0.097, 0.163]
σ^2_{SE}	0.0602	0.0607	0.0934	0.1099	0.1333	0.1454	0.1458
Post. S.D.	(0.0116)	(0.0124)	(0.0100)	(0.0095)	(0.0107)	(0.0114)	0.0114
[*H.D.R.*]	[0.042, 0.080]	[0.041, 0.081]	[0.077, 0.110]	[0.095, 0.126]	[0.117, 0.152]	[0.128, 0.165]	[0.128, 0.166]

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Parameters	$M_1$$^{\lozenge}$	$S^{\dagger} = 1$	$S = 10^3$	$S = 10^4$	$S = 10^5$	$S = 10^7$	M_2
σ^2_{CH}	0.0459	0.0457	0.0619	0.0994	0.2793	0.3819	0.3866
Post. S.D.	(0.0095)	(0.0092)	(0.0104)	(0.0130)	(0.0424)	(0.0174)	0.0175
[*H.D.R.*]	[0.032, 0.063]	[0.032, 0.062]	[0.046, 0.080]	[0.079, 0.121]	[0.195, 0.322]	[0.354, 0.411]	[0.359, 0.416]
σ^2_{TR}	0.0564	0.0577	0.0504	0.0504	0.1121	0.1086	0.1085
Post. S.D.	(0.0233)	(0.0240)	(0.0191)	(0.0179)	(0.0362)	(0.0322)	0.0319
[*H.D.R.*]	[0.024, 0.099]	[0.024, 0.100]	[0.025, 0.086]	[0.027, 0.084]	[0.064, 0.180]	[0.065, 0.168]	[0.066, 0.167]
σ^2_{UK}	0.4026	0.4103	0.4136	0.4499	0.5074	0.5475	0.5486
Post. S.D.	(0.0500)	(0.0461)	(0.0427)	(0.0419)	(0.0400)	(0.0423)	0.0423
[*H.D.R.*]	[0.311, 0.477]	[0.330, 0.480]	[0.342, 0.482]	[0.383, 0.520]	[0.446, 0.577]	[0.482, 0.620]	[0.483, 0.621]

Notes:
∗ Highest Density Region.
◊ Based on national frontiers (M1).
†S^i stands for a scale factor of order 10^i.

Posterior moments are computed based on 50,000 points generated from the Gibbs sampling algorithm. The end points of the 90% confidence region are the 5^{th} and the 95^{th} percentiles of the posterior marginal densities.

7.4 Posterior Marginal Densities and Convergence Paths for λ, Efficiency Score and σ^2

For completeness, in this section we include the plots for λ (figures 7.29 through 7.42), efficiency score (figures 7.43 through 7.56) and σ^2 (figures 7.29 through 7.42) to support the idea that as the prior strength on the hybrid model is increased, we are continuously moving from model M1 to model M2.

7.4.1 λ

When analyzing the plots for λ (figures 7.29 through 7.42), a few things should be noted.

Posterior marginal densities for M1 and the hybrid model with weak prior (M3 with $S = 1$) overlap perfectly for most of the countries (with the exception of United Kingdom, Sweden, Romania, Turkey and Croatia). On the one hand this can be explained by the smaller number of observations that Romania, Turkey and Croatia have and on the other hand, by the different nature of the priors used in model M1 and M3 that can lead to such small discrepancies. In the case of United Kingdom, the almost bimodal look of the density might be explained by the presence of clusters of banks in the data.

Posterior marginal densities for M2 and the hybrid model with very strong prior ($S = 10^9$) superimposed support the idea of model convergence.

The convergence path is direct for all countries with the exception of Turkey and Germany as noted from the results tables. The most likely explanation for this is the fact that for Turkey and Germany there is a very small change in the posterior means' values for λ making them appear more sensitive to the prior's strength, due to the scale of the axis.

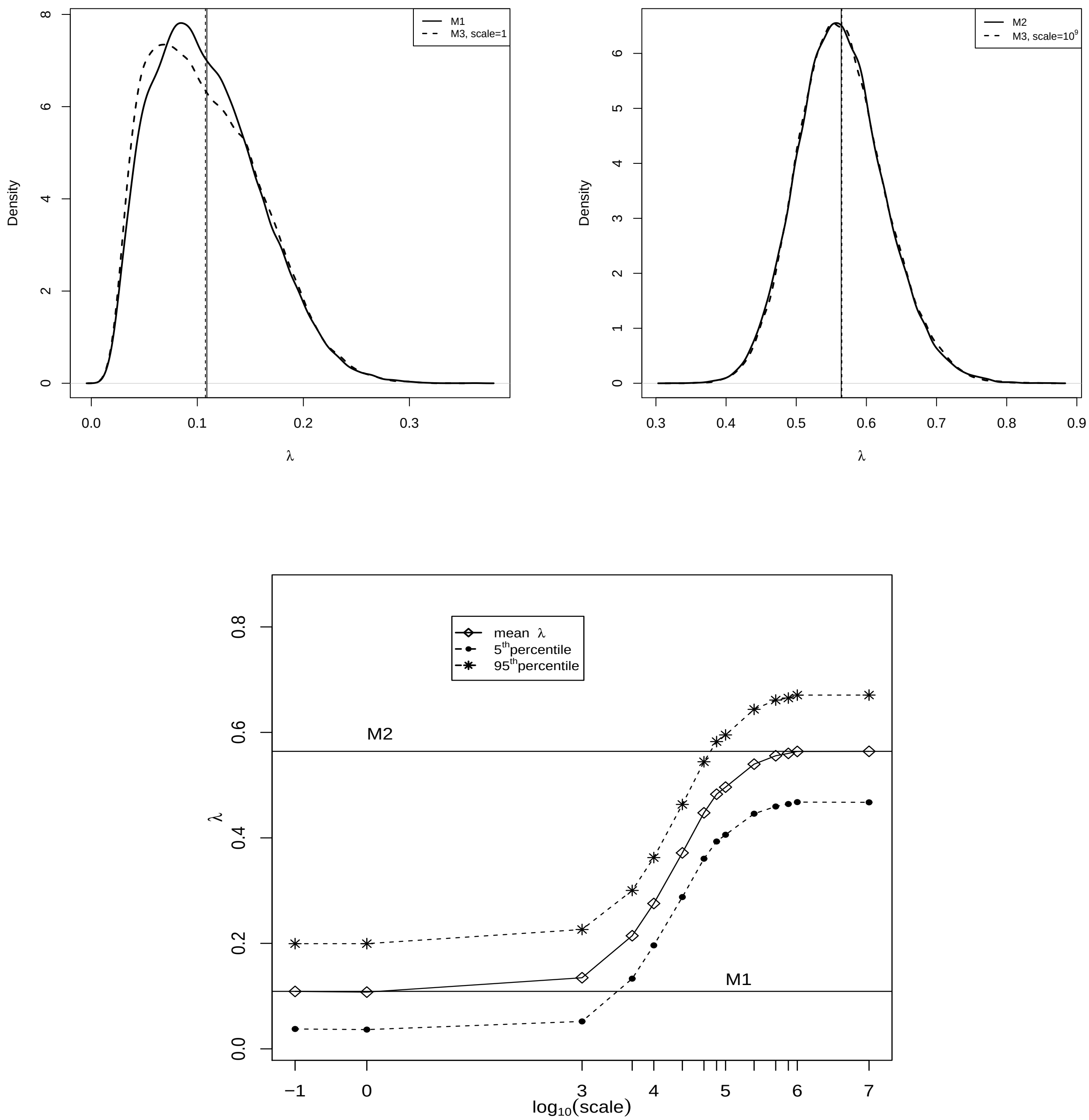

Figure 7.29: Croatia - Model Convergence, λ.

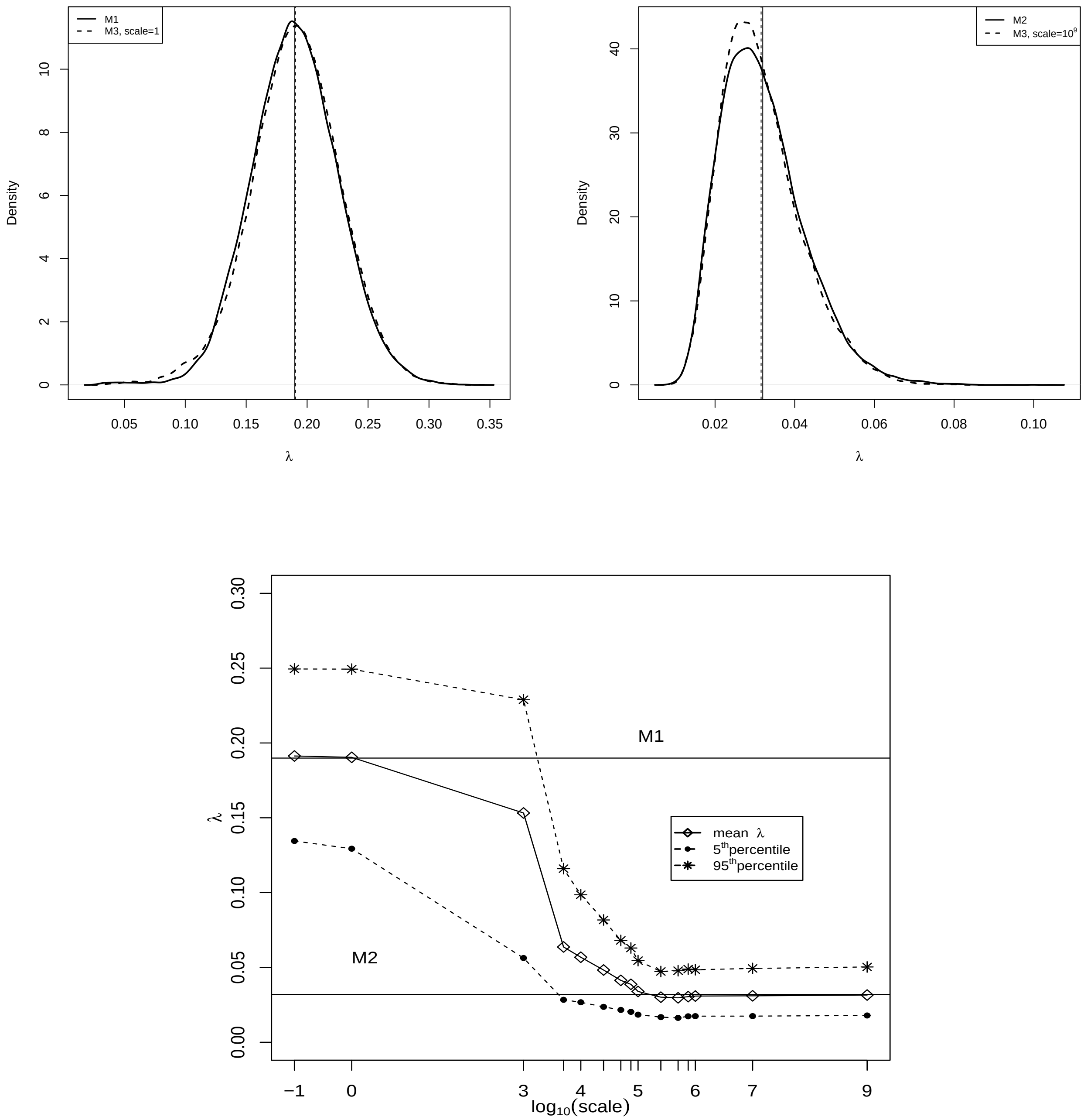

Figure 7.30: Denmark - Model Convergence, λ.

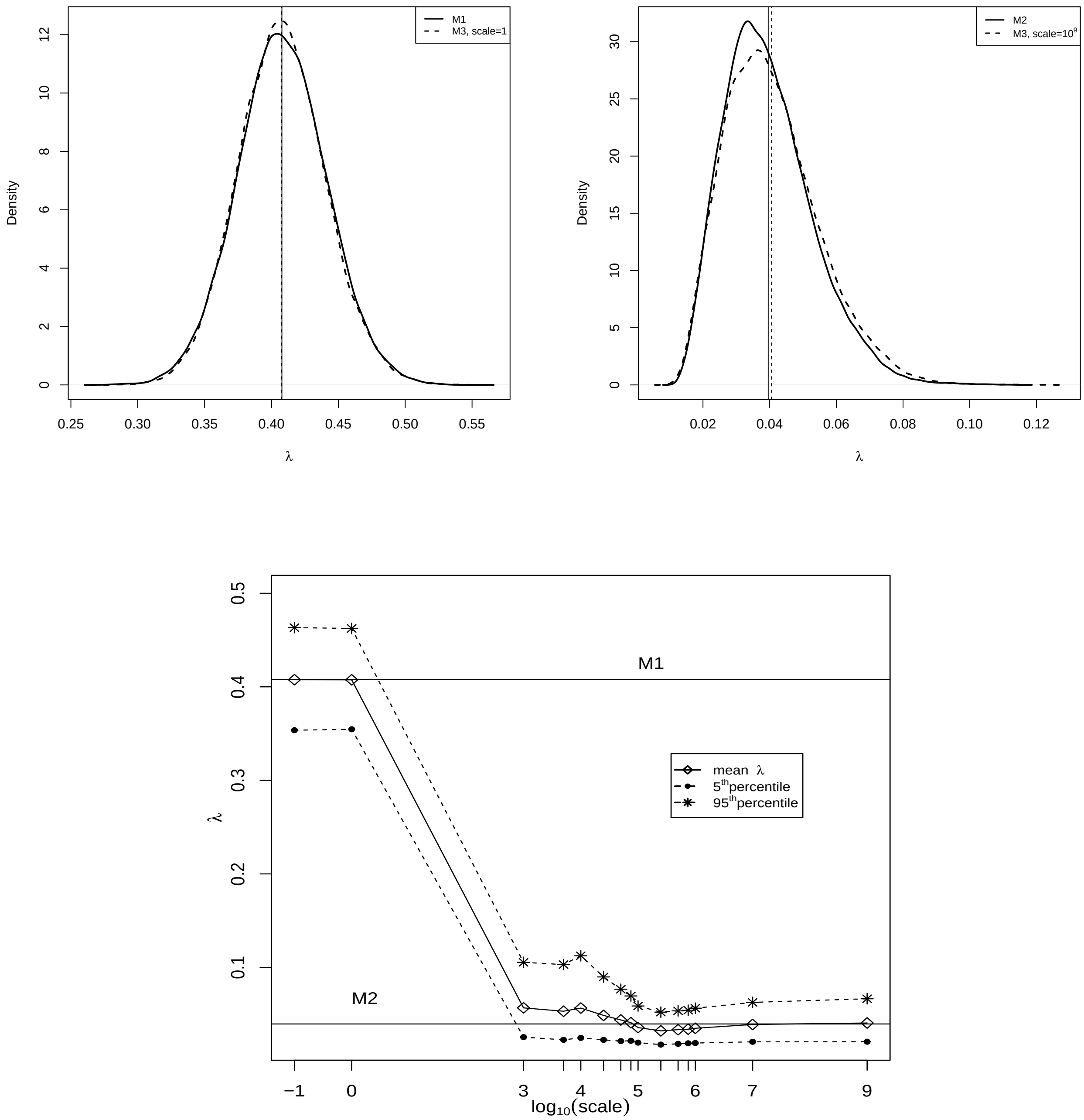

Figure 7.31: France - Model Convergence, λ.

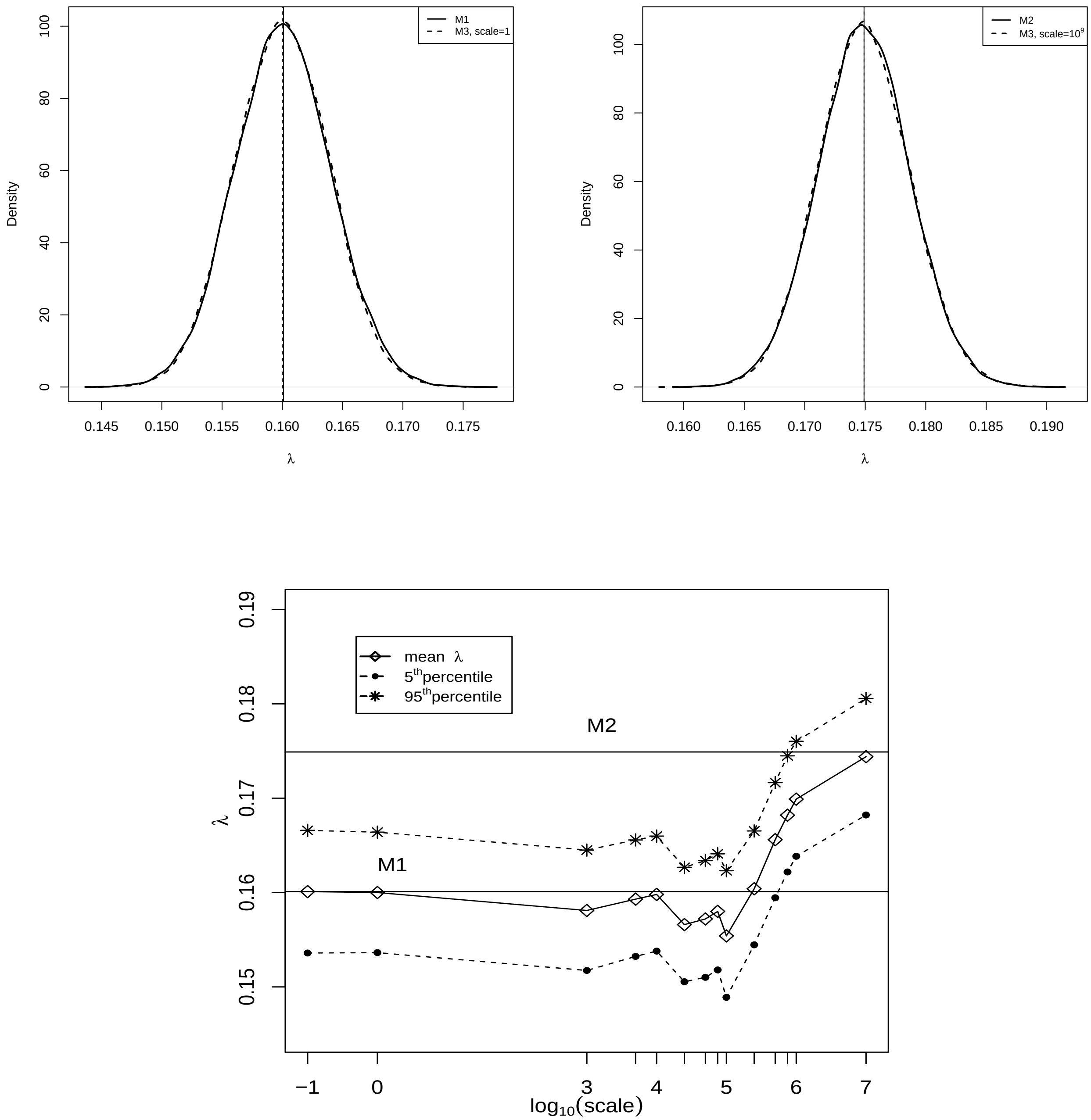

Figure 7.32: Germany - Model Convergence, λ.

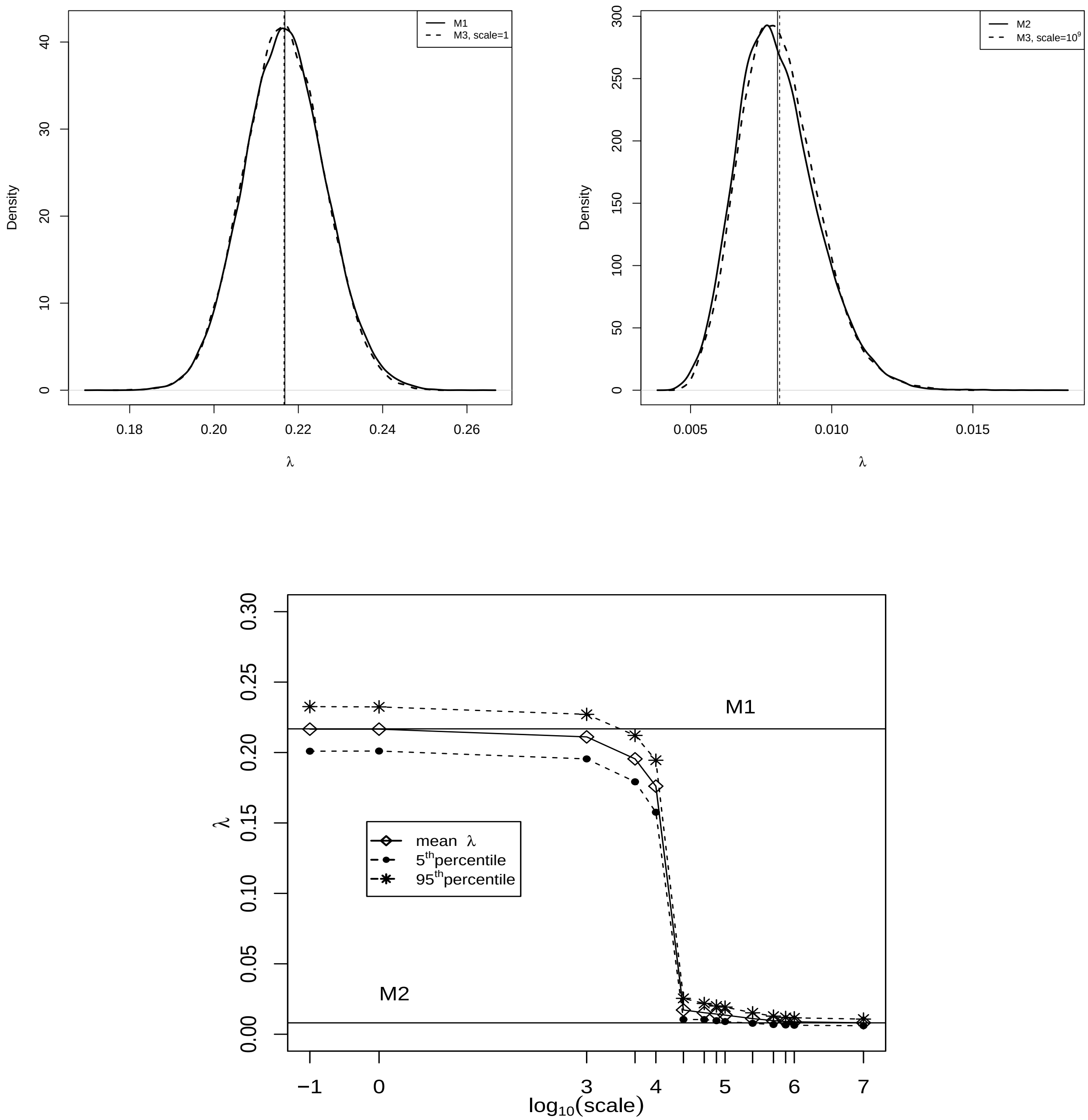

Figure 7.33: Italy - Model Convergence, λ.

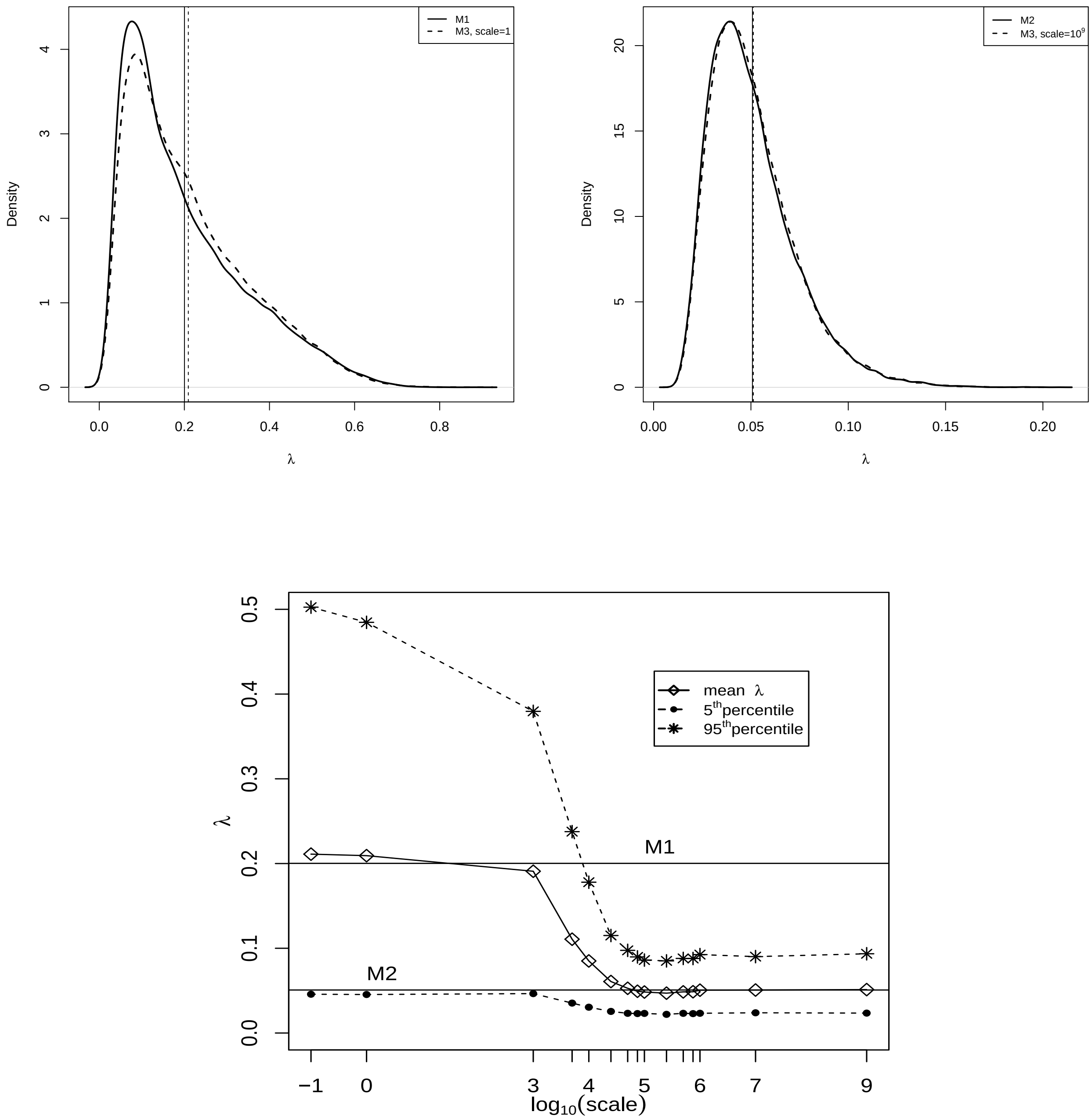

Figure 7.34: Netherlands - Model Convergence, λ.

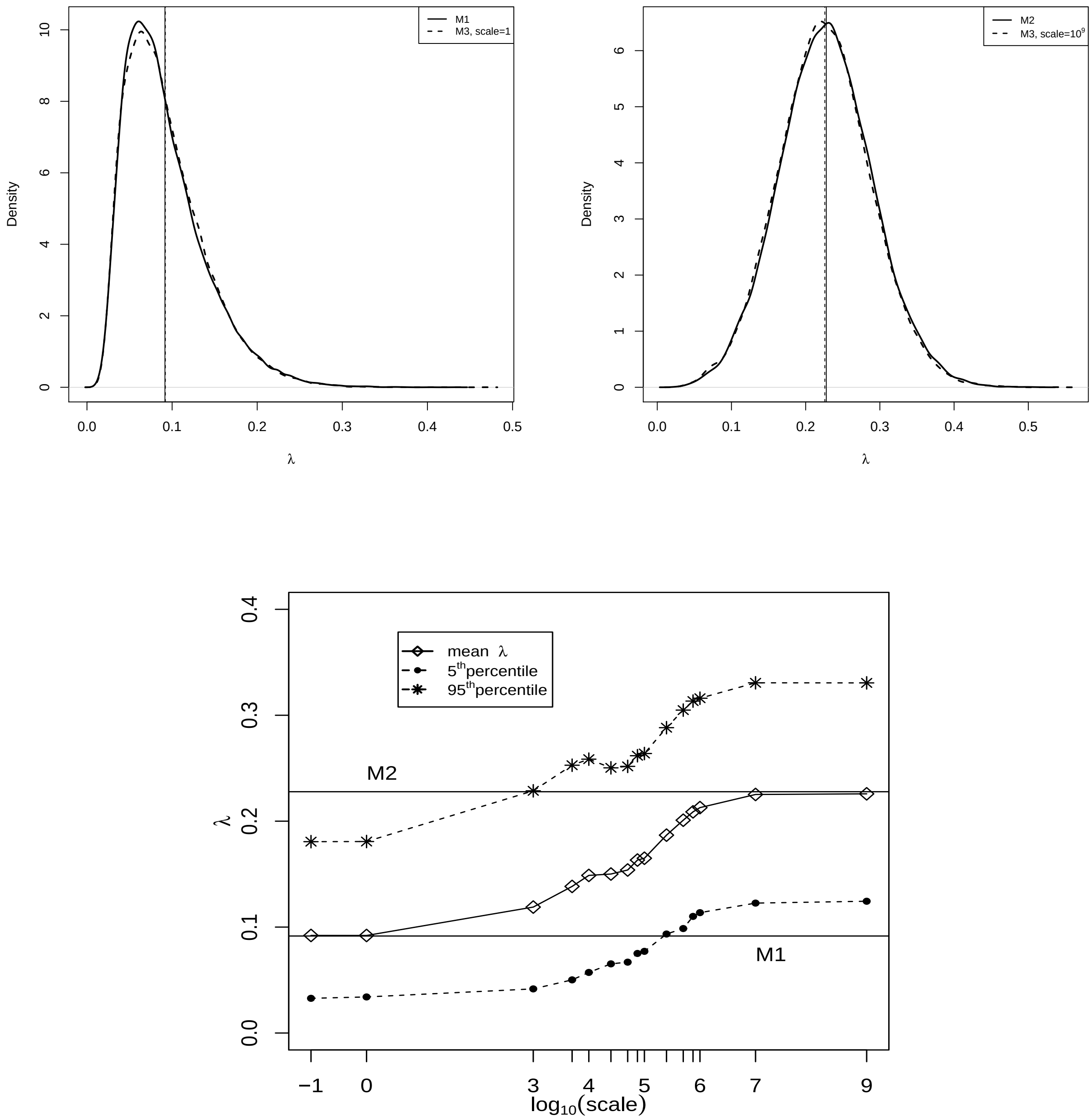

Figure 7.35: Poland - Model Convergence, λ.

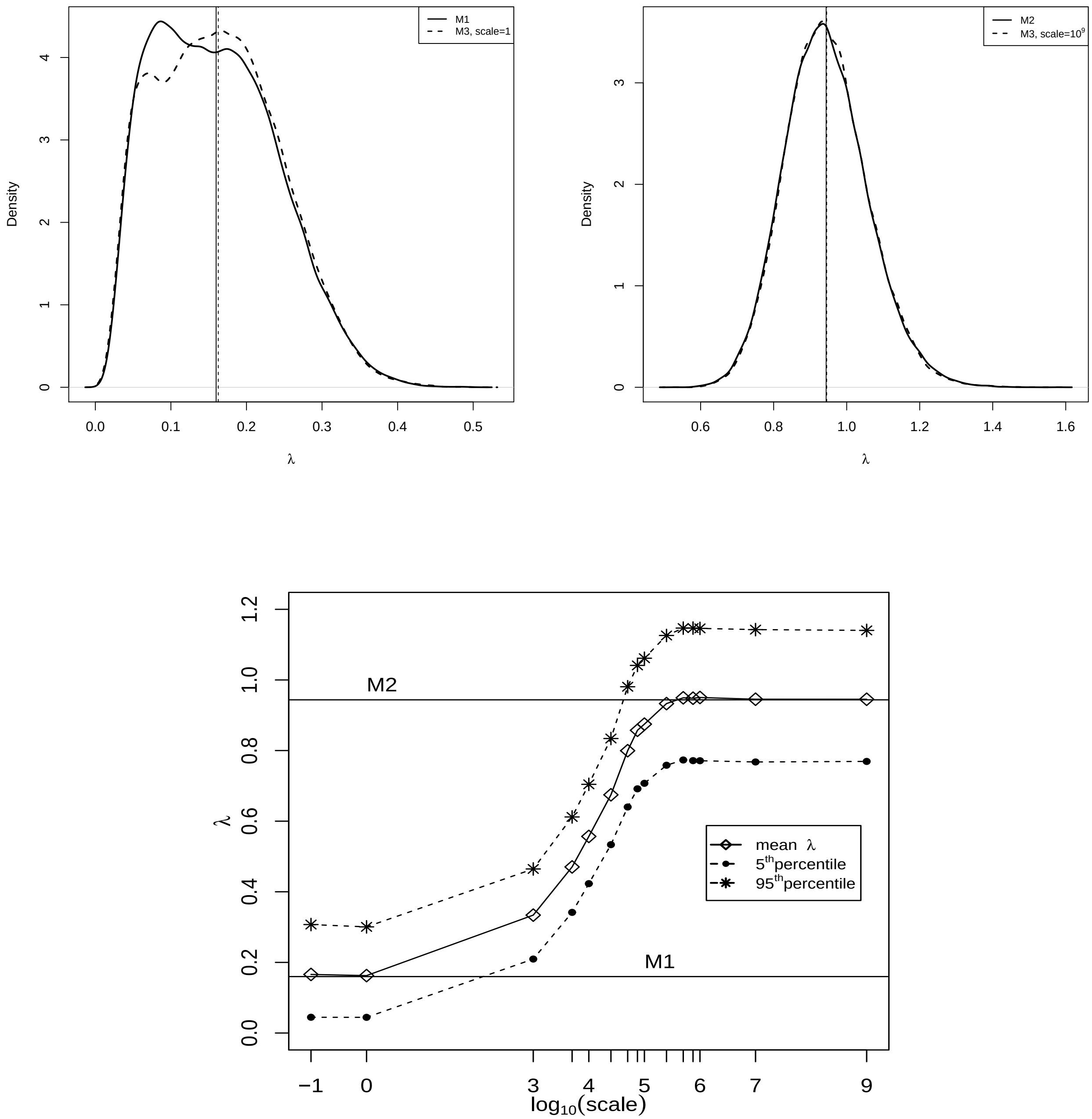

Figure 7.36: Romania - Model Convergence, λ.

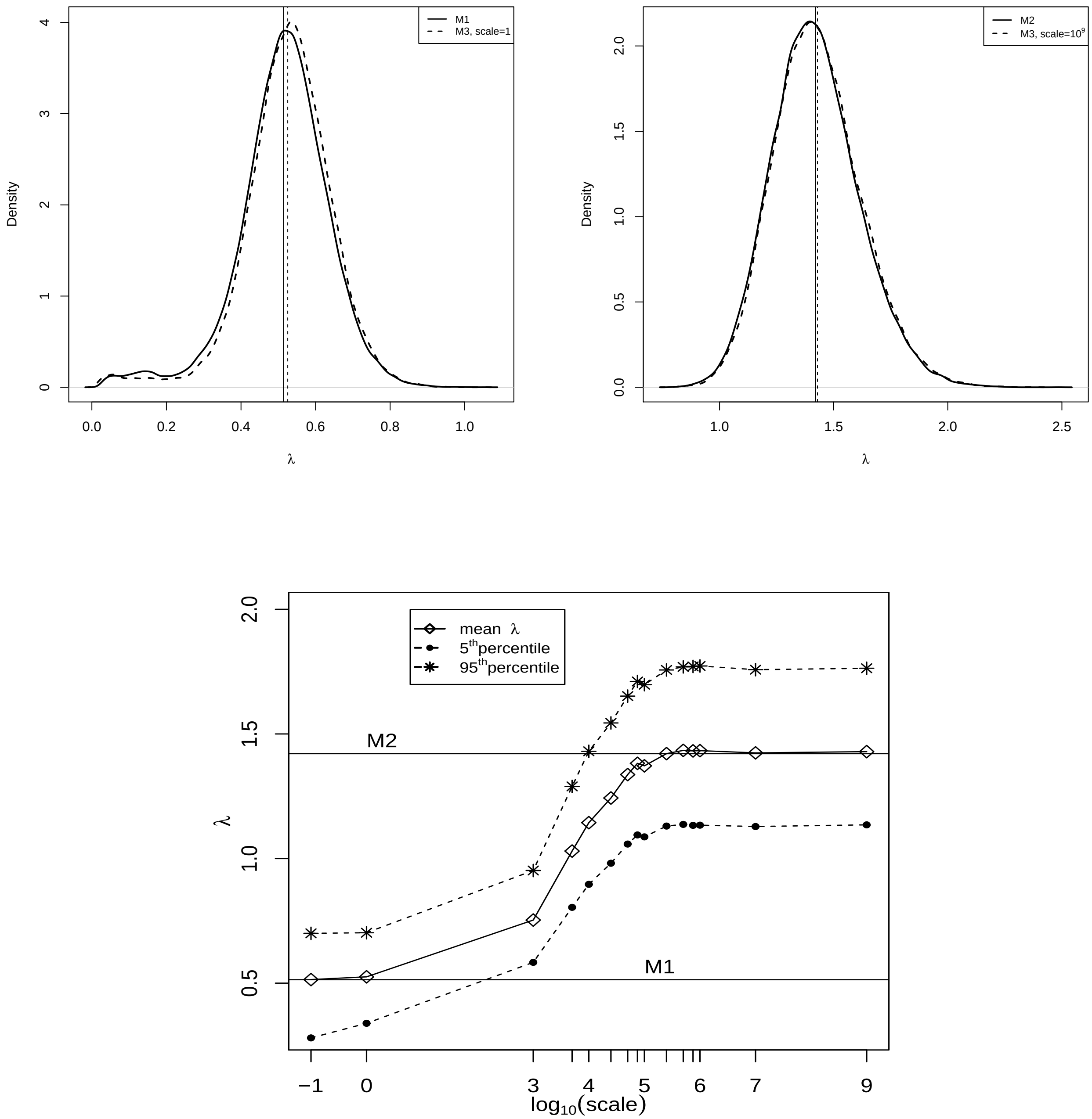

Figure 7.37: Serbia - Model Convergence, λ.

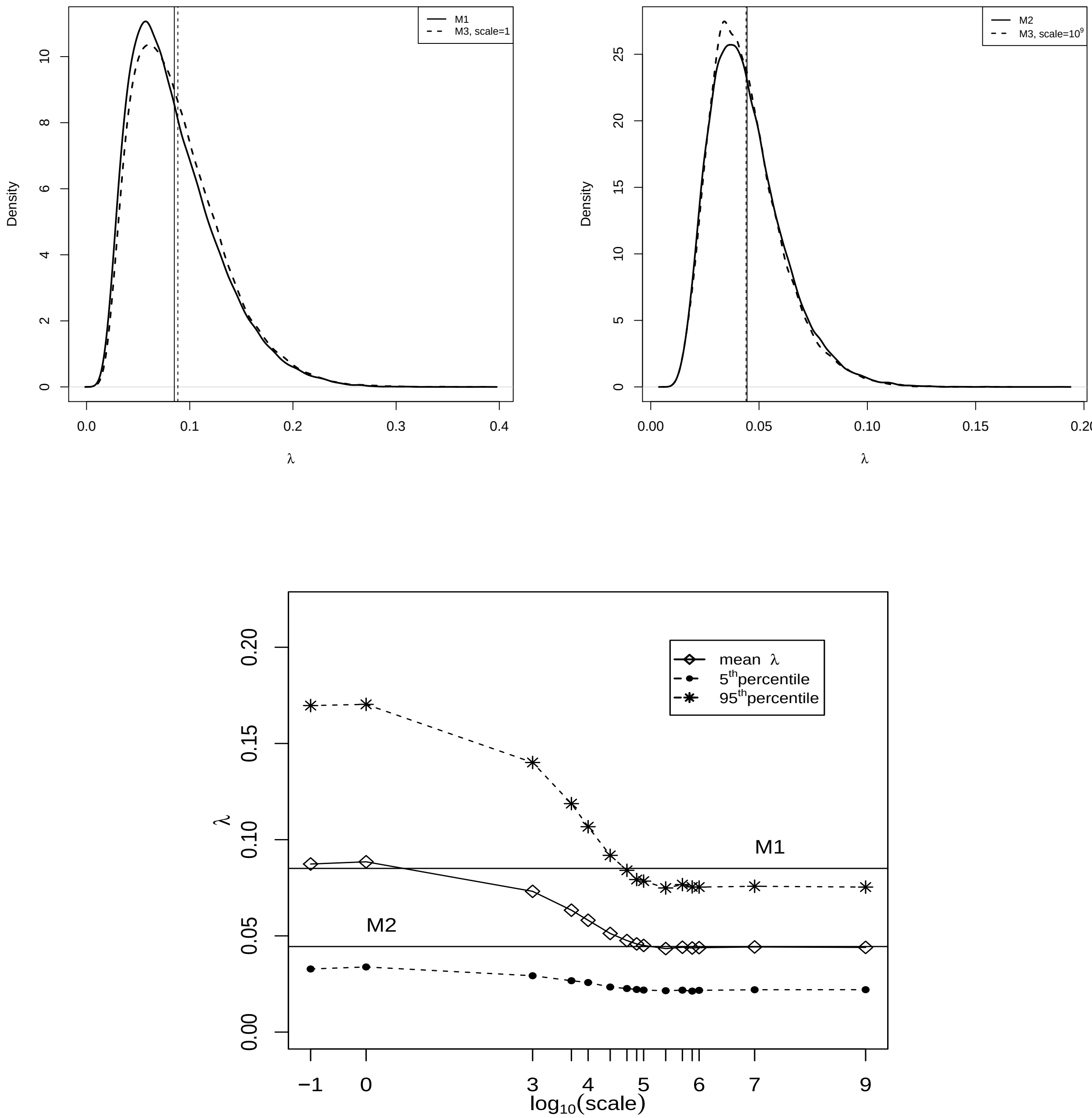

Figure 7.38: Slovenia - Model Convergence, λ.

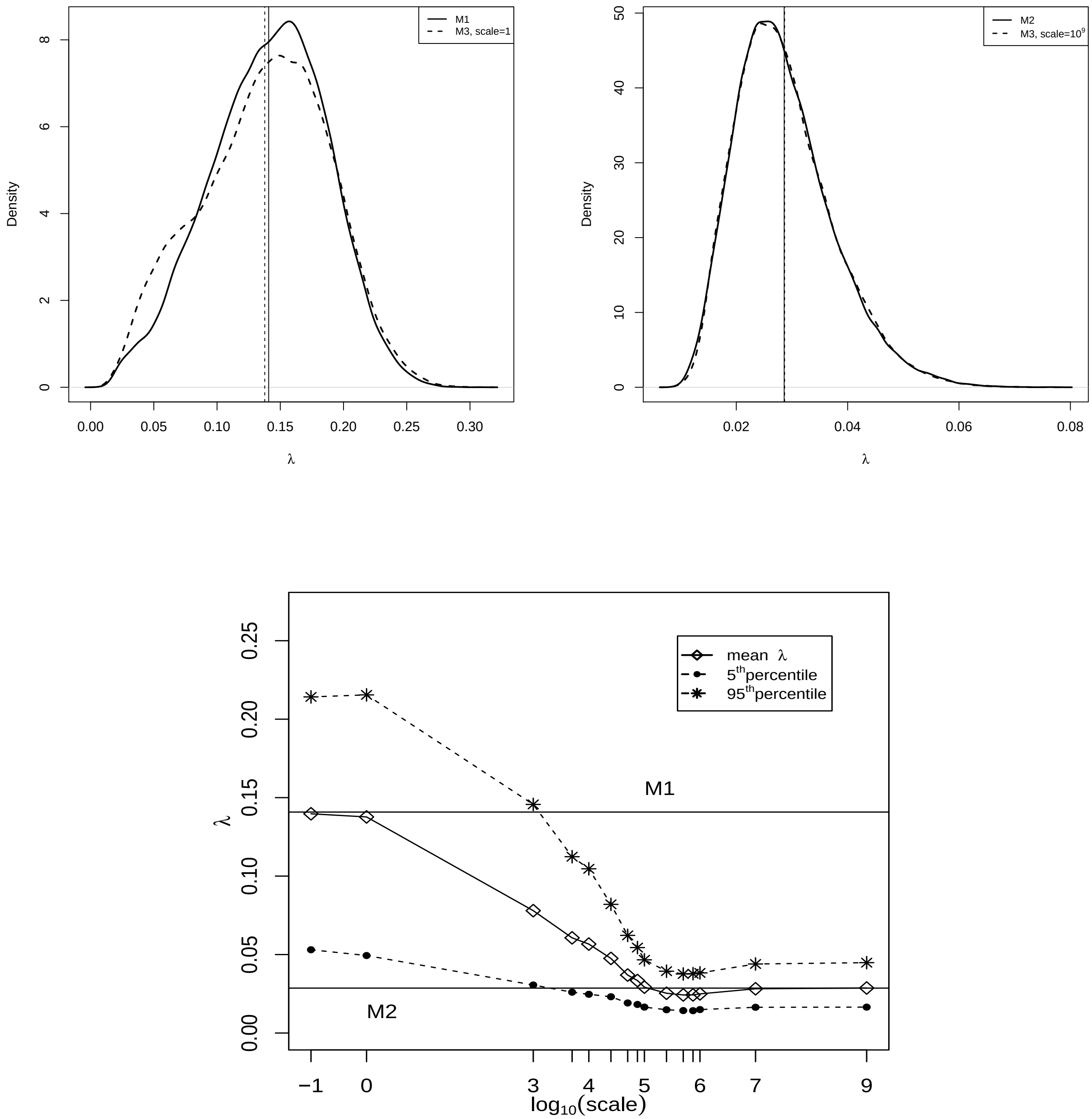

Figure 7.39: Sweden - Model Convergence, λ.

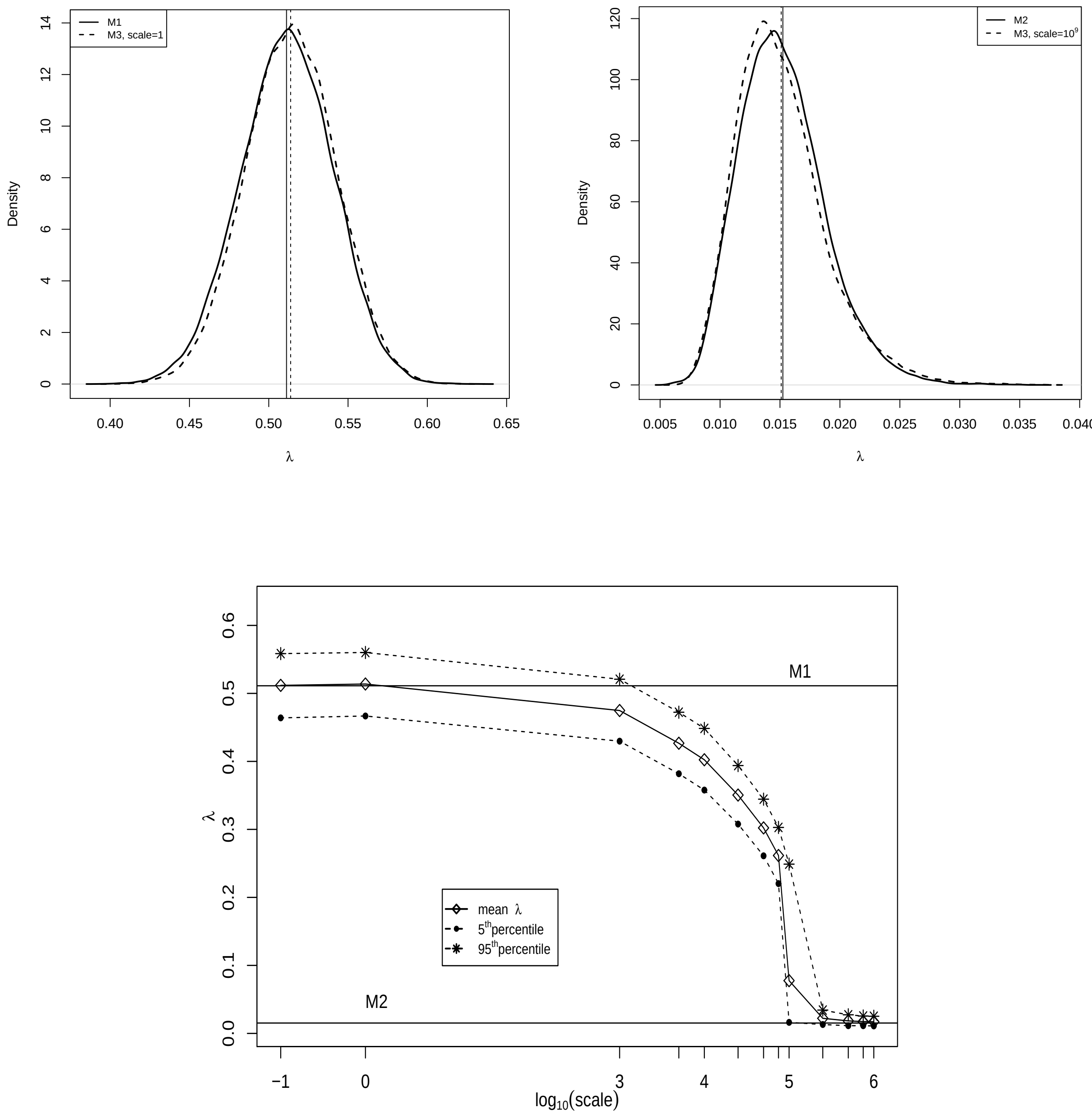

Figure 7.40: Switzerland - Model Convergence, λ.

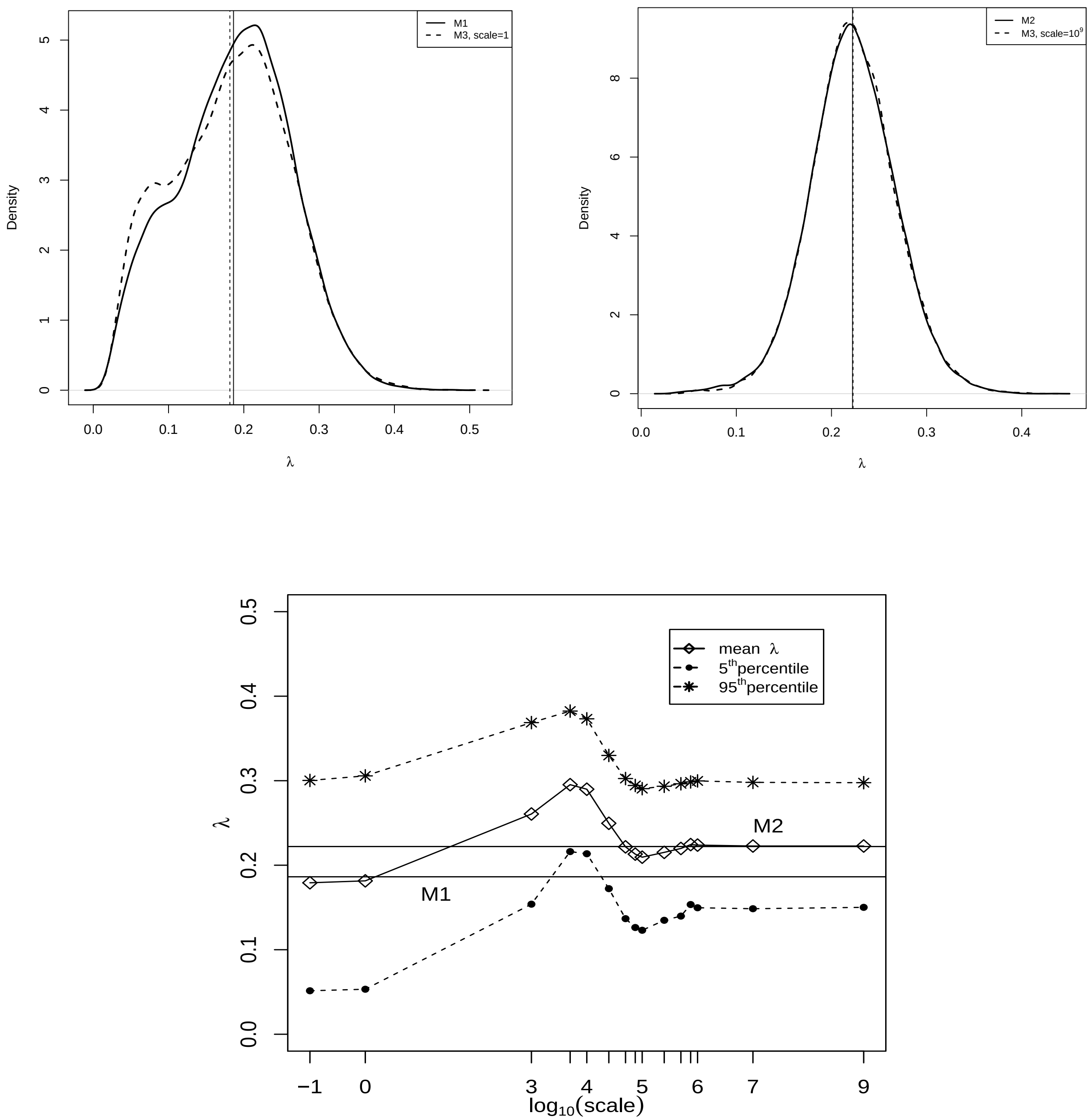

Figure 7.41: Turkey - Model Convergence, λ.

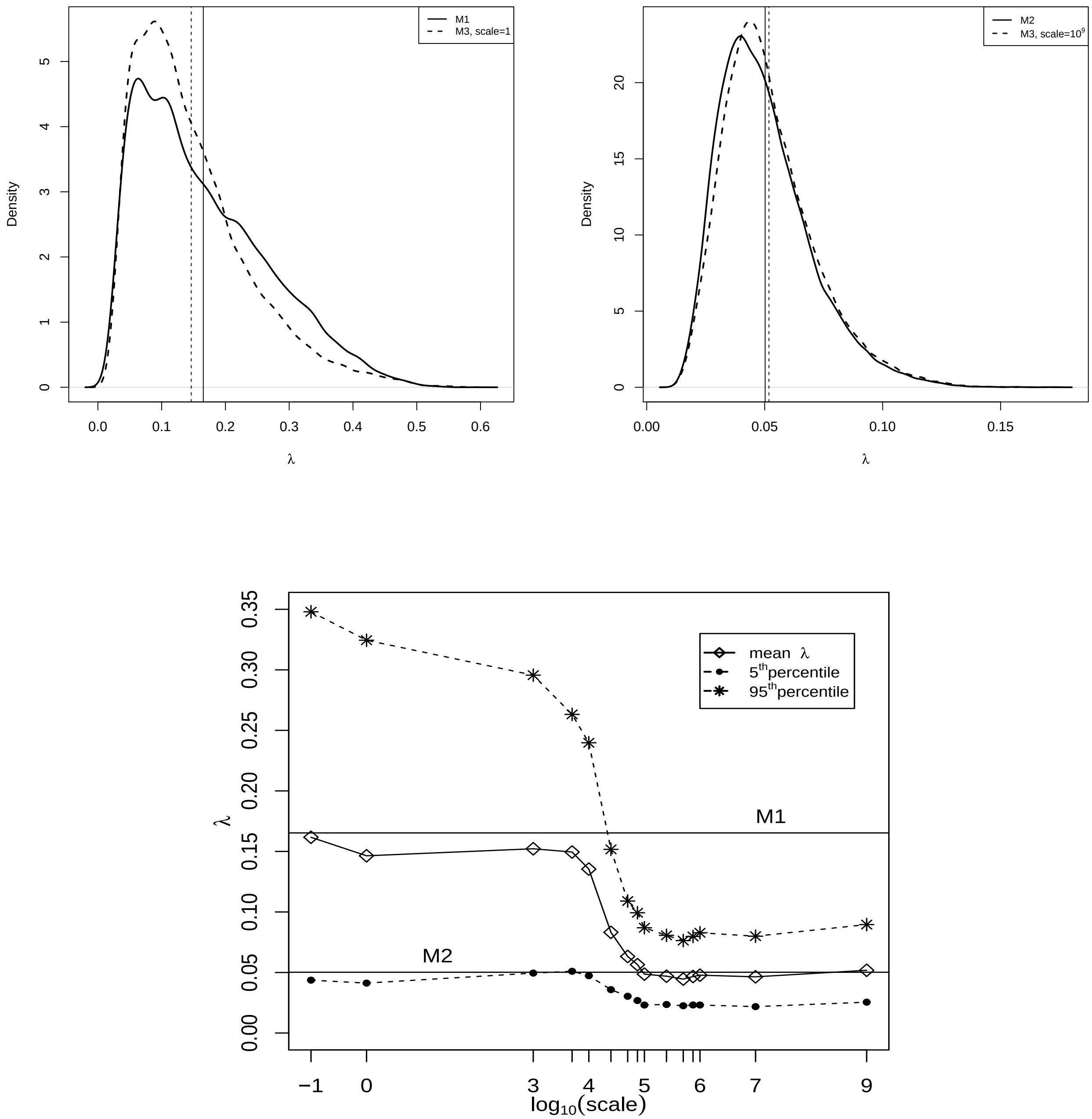

Figure 7.42: United Kingdom - Model Convergence, λ.

7.4.2 Efficiency Score

The efficiency score is a function of λ ($r = \exp(-\lambda)$ and $\bar{r} = \mathrm{E}[\exp(-\lambda)]$), and looking at the convergence plots for r (figures 7.43 through 7.56), we observe the same trends as we did for λ.

Turkey and Germany are the only countries for which the convergence path is indirect. They are also countries with very small variation in the posterior means of the efficiency score, which means that as the prior strength changes, even the smallest variation in the efficiency score would look significant as there is not much room for movement to begin with.

While the posterior marginal densities for M1 and M3 with weak prior ($S = 1$) do not overlap perfectly in the case of Romania, Netherlands, Croatia, Sweden, United Kingdom or Turkey, the differences are so small that we can still conclude that there is convergence. The discrepancies can be explained either by the small number of observations in the case of some of these countries (Romania, Croatia, etc.) or by the different nature of the priors used in model M1 as opposed to model M3. As mentioned before, some of the countries (like United Kingdom) might have some clustering in the data.

In some cases, it takes a relatively weak prior to cause movement from M1 towards M2 (i.e. France), but in many situations (i.e. Switzerland), the transition graphs show a sluggish convergence as it takes very strong prior to cause adjustments in the parameter's value.

Slow convergence can be an indicator that there is enough evidence in the data against the assumption of a common frontier. When fast convergence is achieved (we see rapid movement in the parameter's values for weak priors), we should take under consideration the fact that for small datasets, the prior might "dominate" the data. In other words, with little information from the data, the results might be driven by the prior (i.e. Serbia).

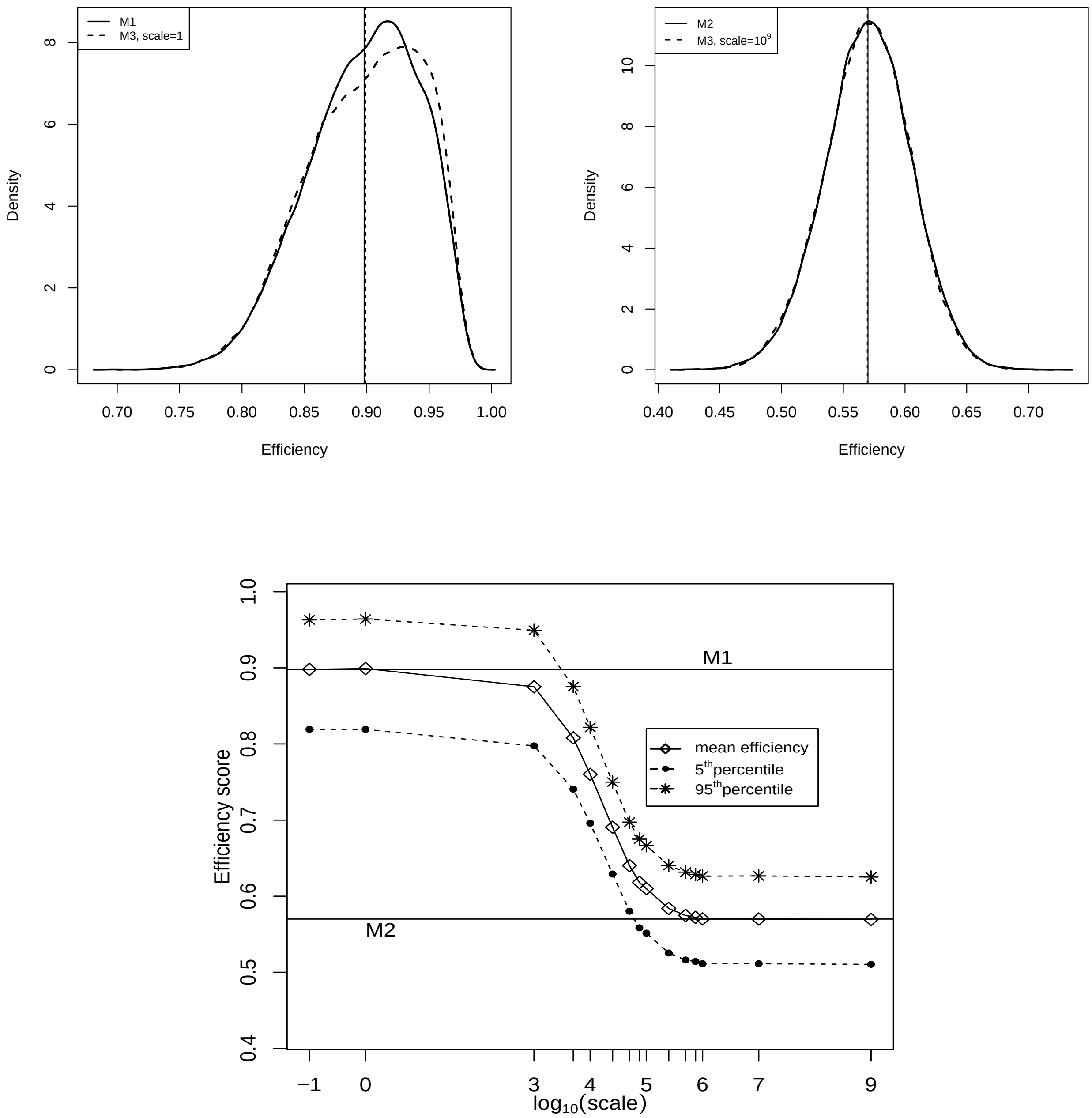

Figure 7.43: Croatia - Model Convergence, Efficiency Score.

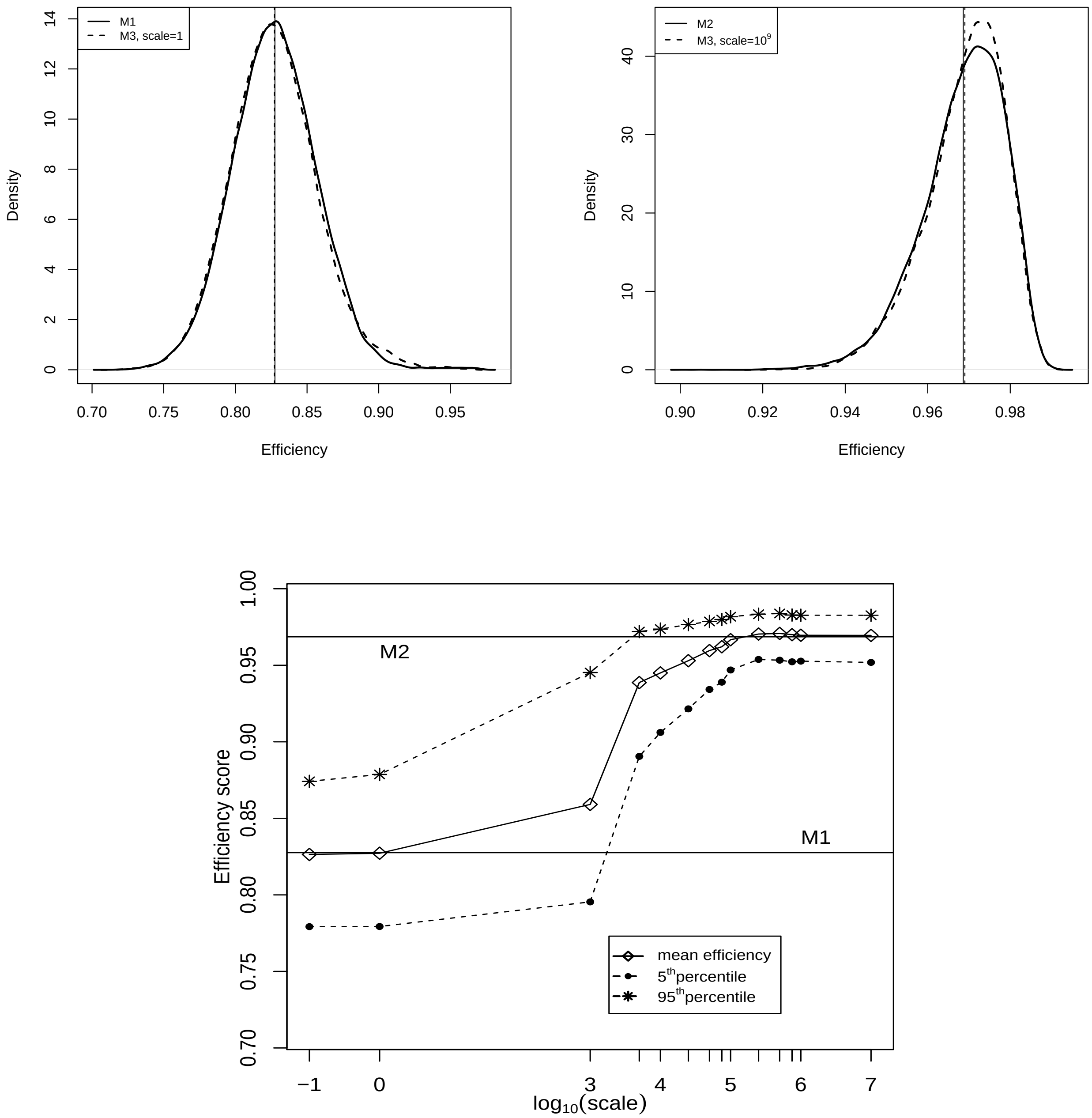

Figure 7.44: Denmark - Model Convergence, Efficiency Score.

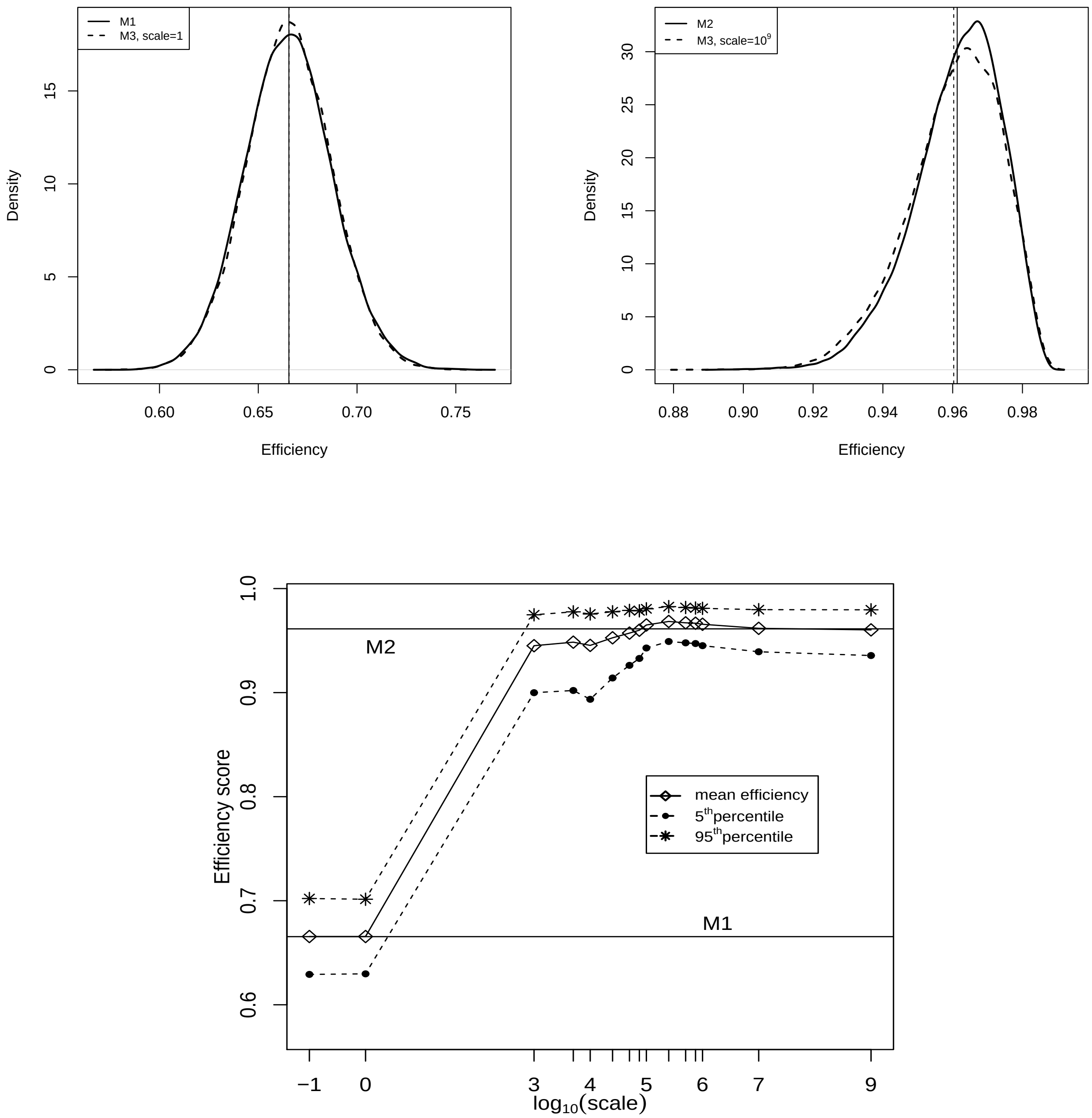

Figure 7.45: France - Model Convergence, Efficiency Score.

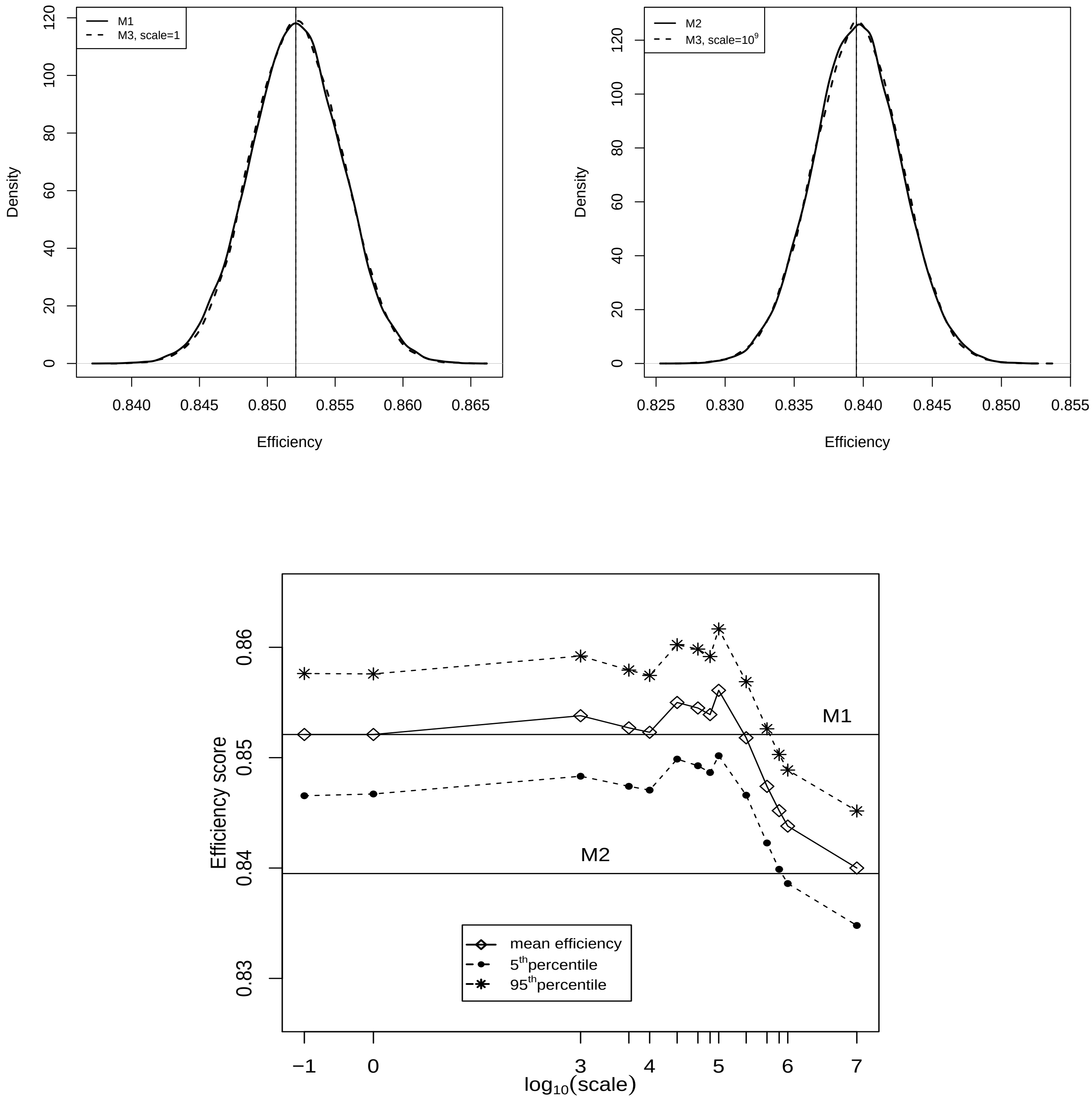

Figure 7.46: Germany - Model Convergence, Efficiency Score.

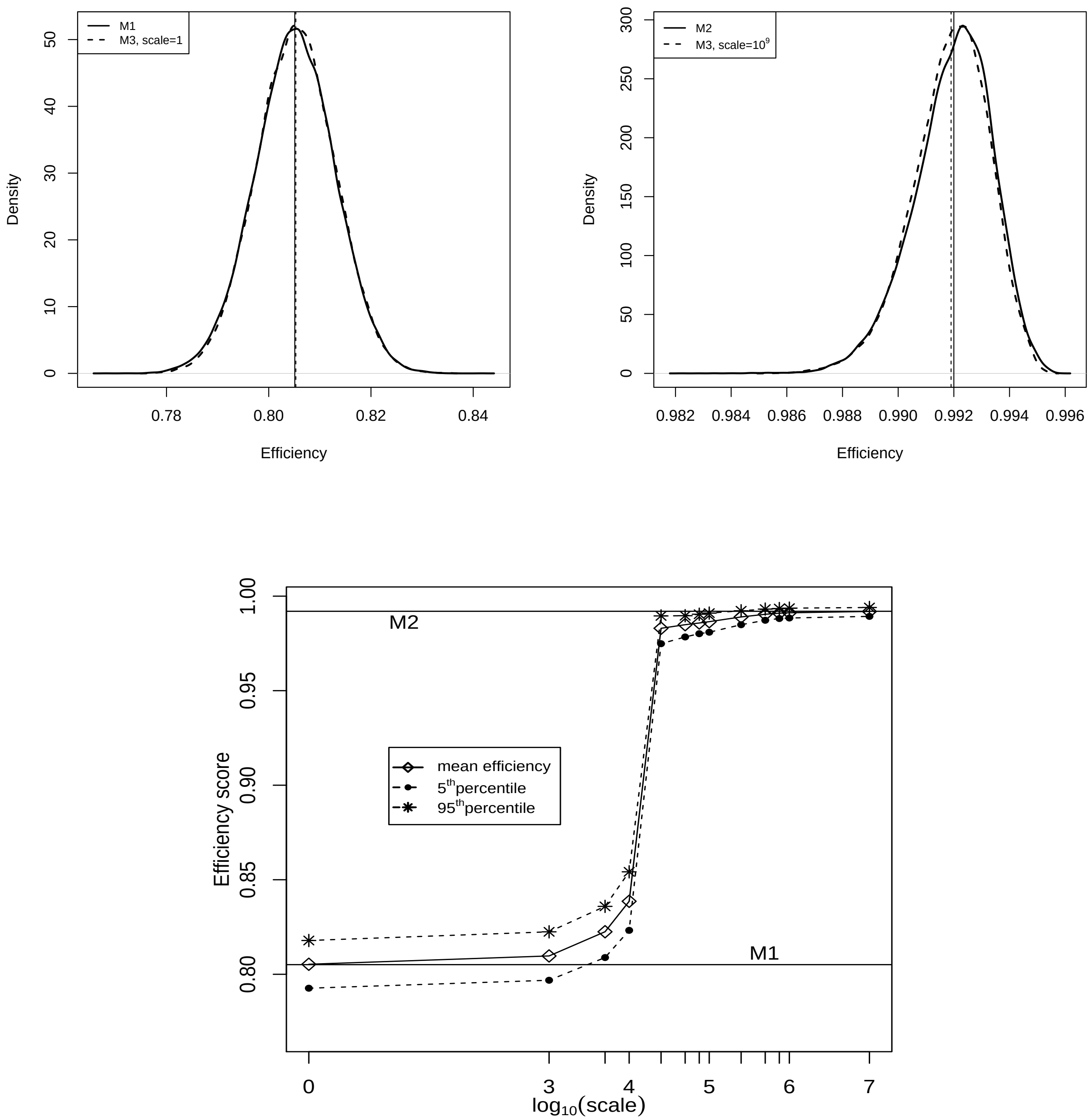

Figure 7.47: Italy - Model Convergence, Efficiency Score.

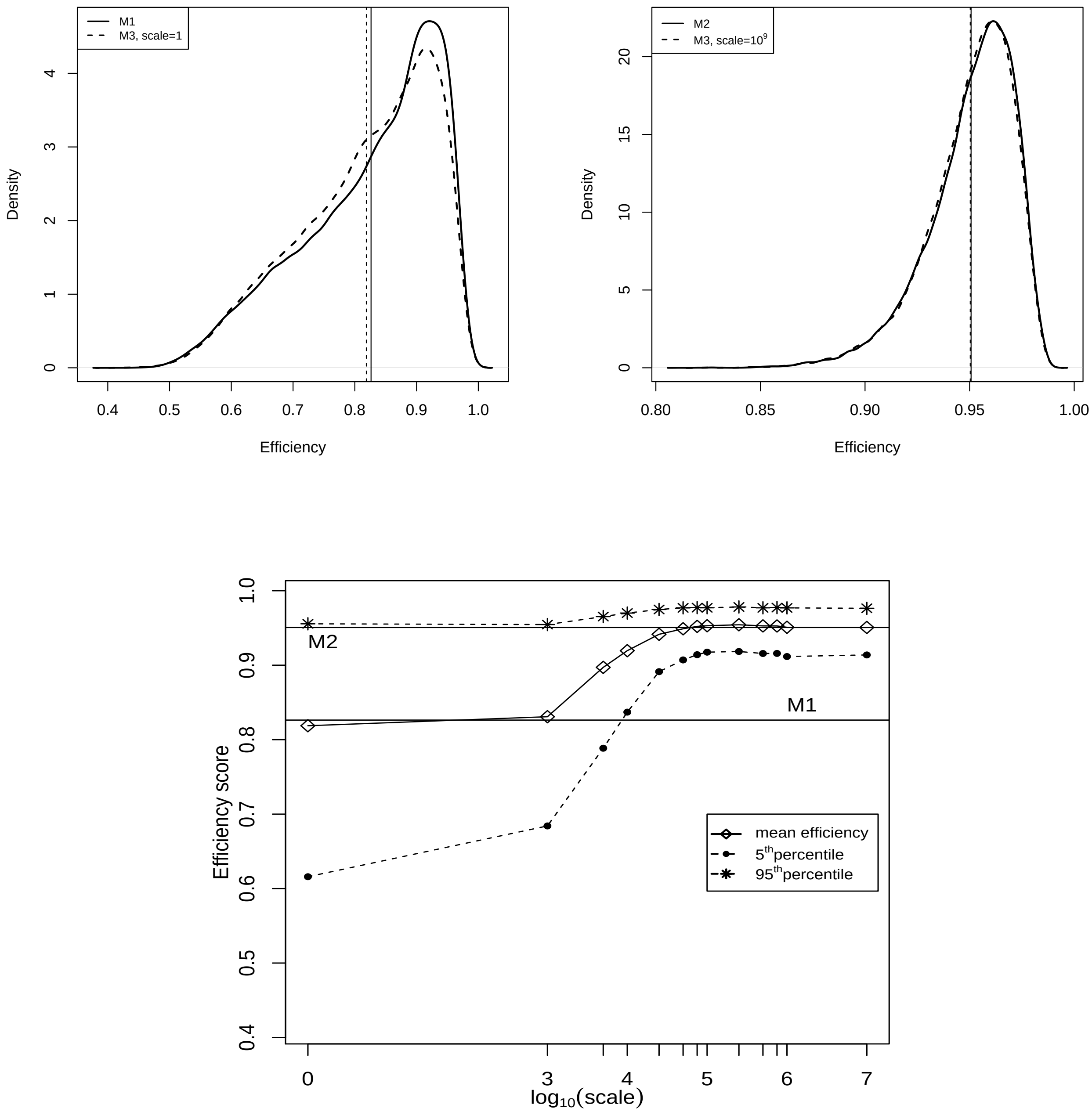

Figure 7.48: Netherlands - Model Convergence, Efficiency Score.

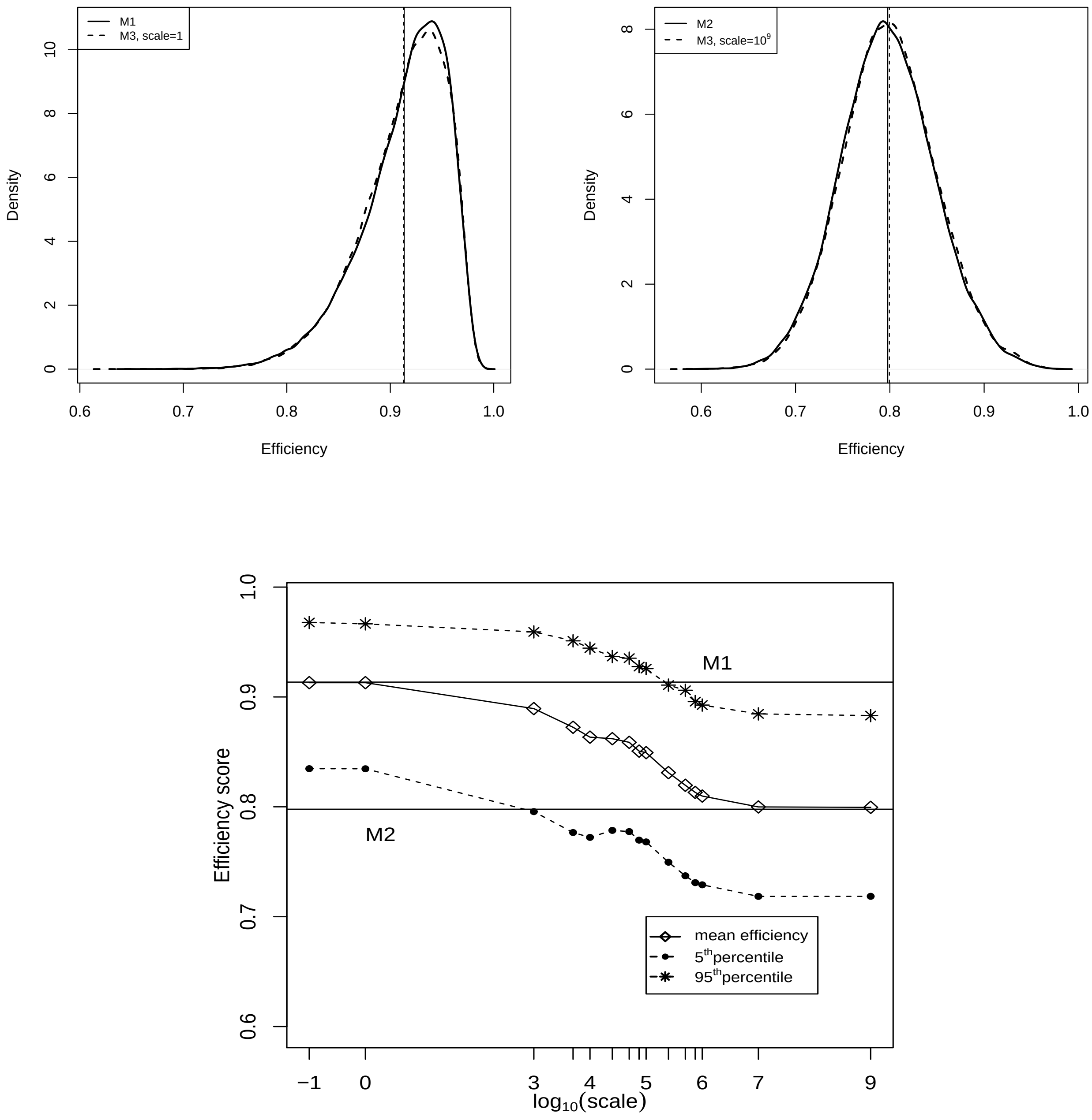

Figure 7.49: Poland - Model Convergence, Efficiency Score.

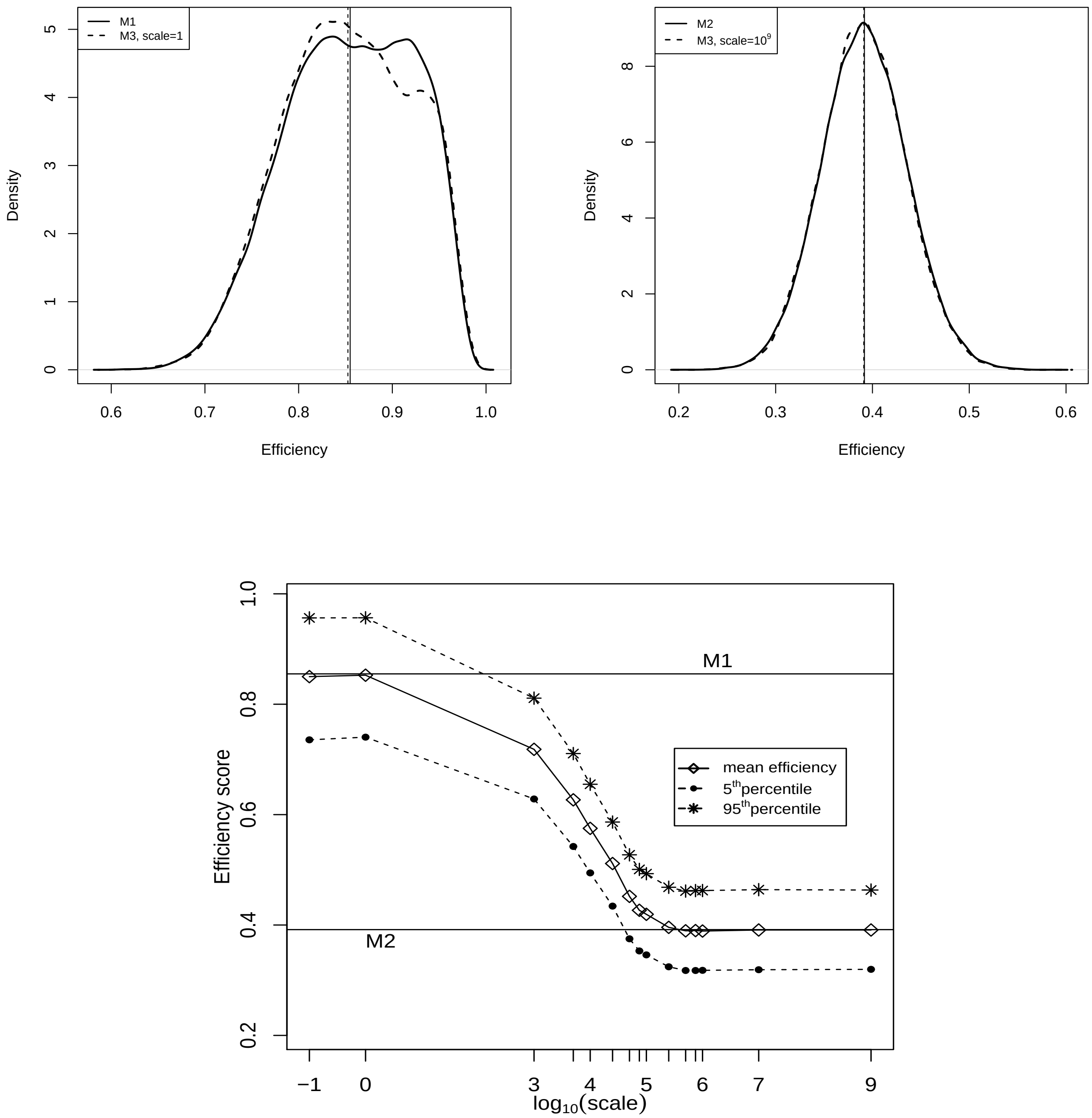

Figure 7.50: Romania - Model Convergence, Efficiency Score.

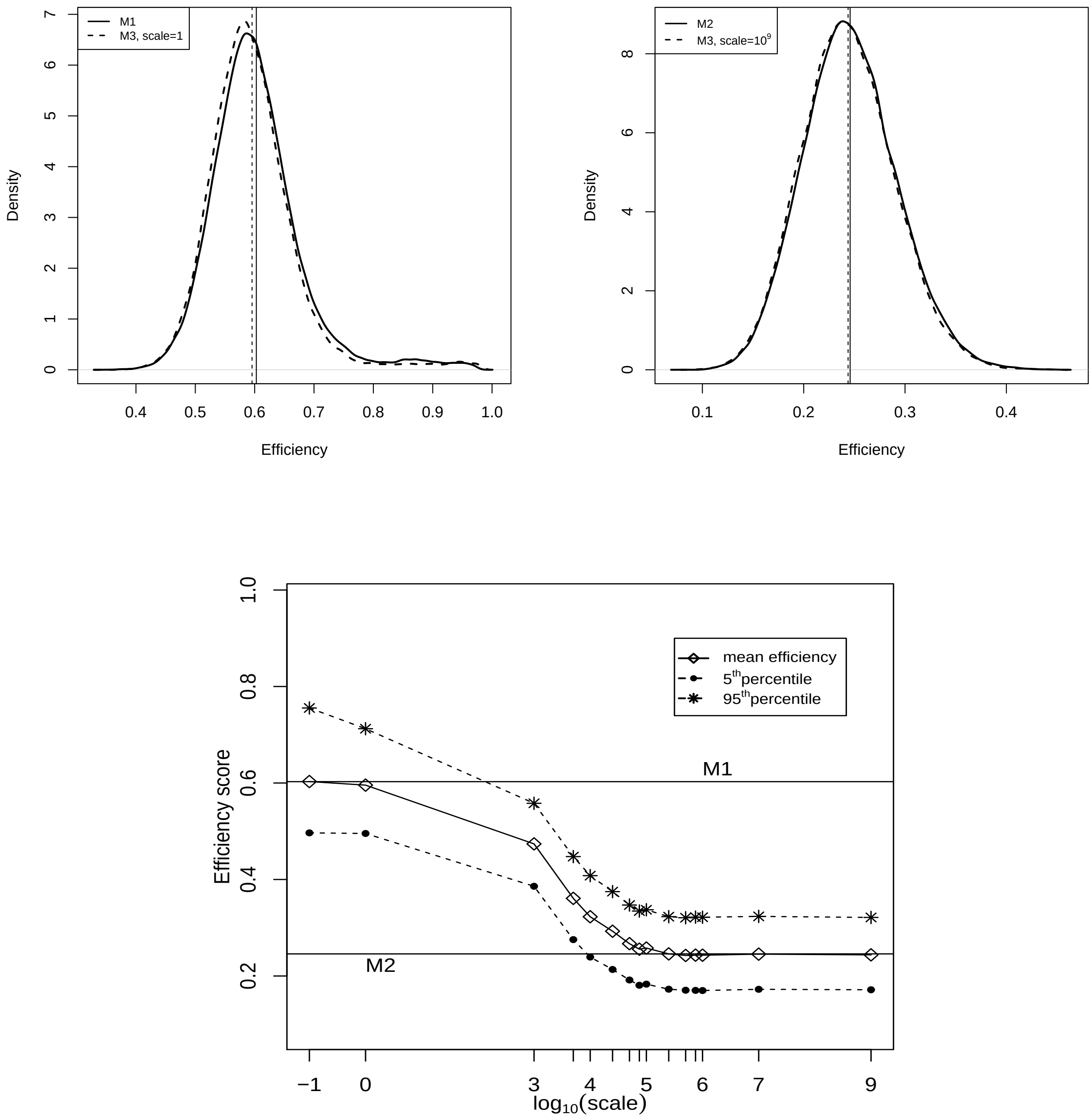

Figure 7.51: Serbia - Model Convergence, Efficiency Score.

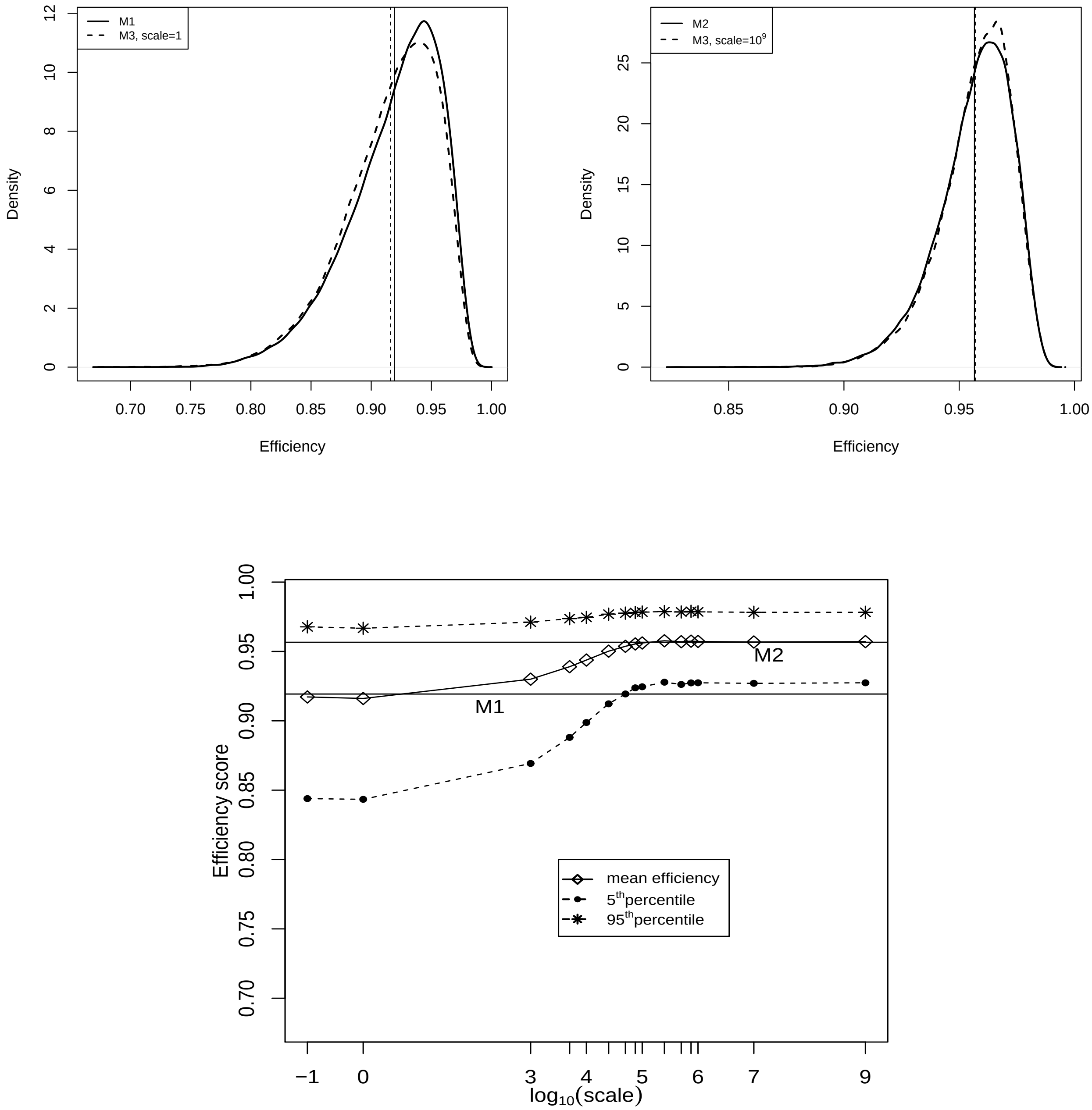

Figure 7.52: Slovenia - Model Convergence, Efficiency Score.

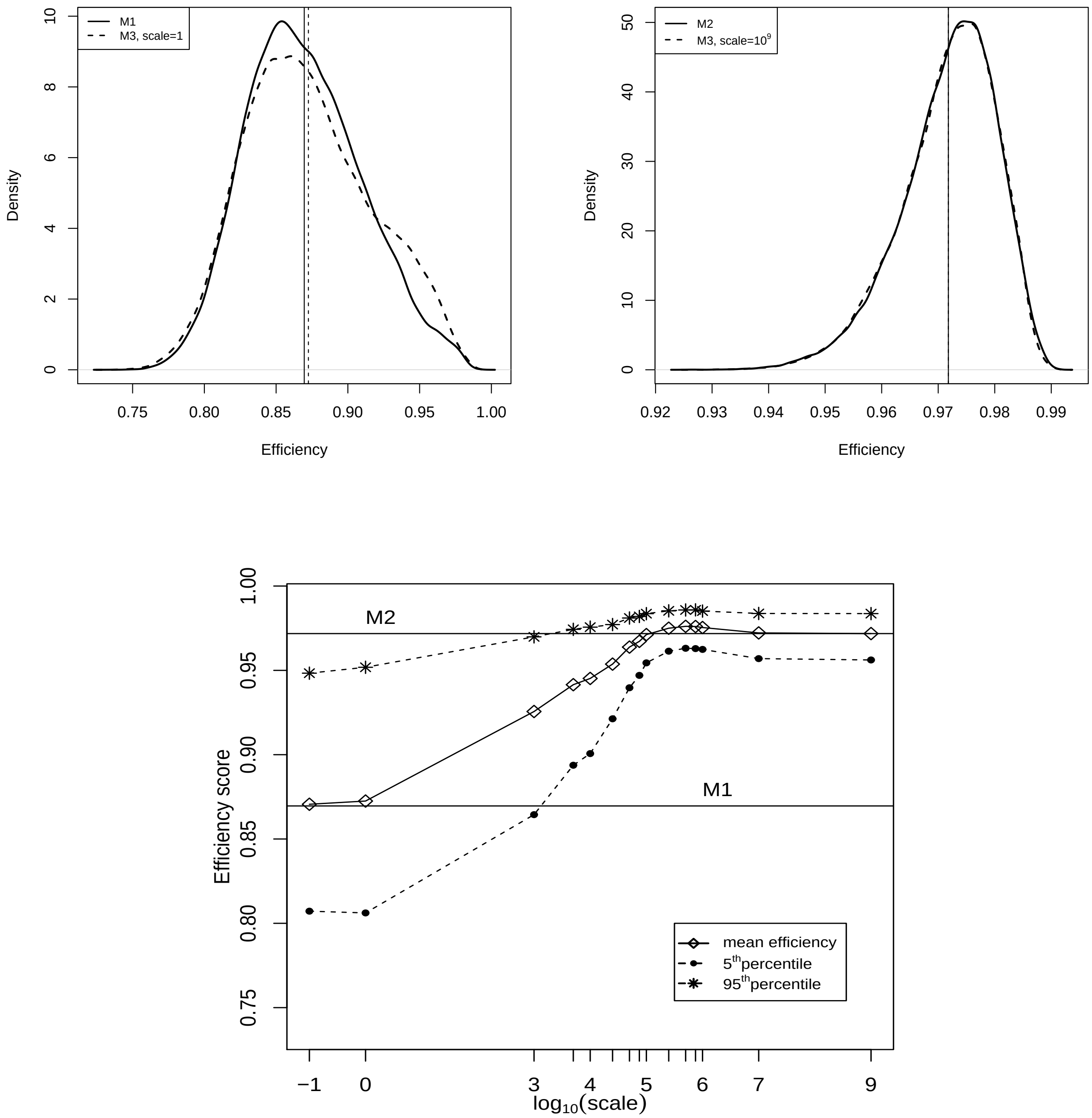

Figure 7.53: Sweden - Model Convergence, Efficiency Score.

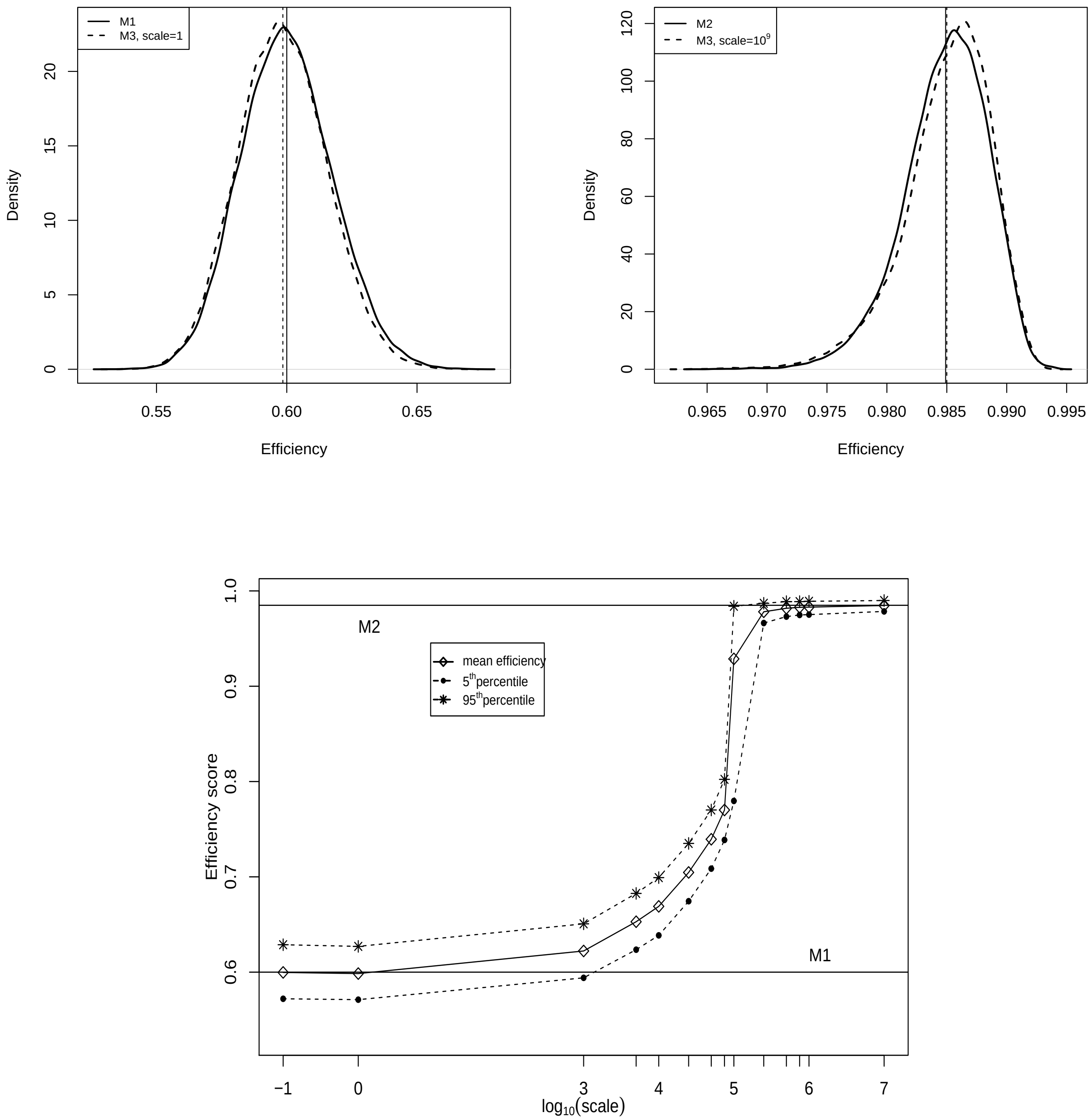

Figure 7.54: Switzerland - Model Convergence, Efficiency Score.

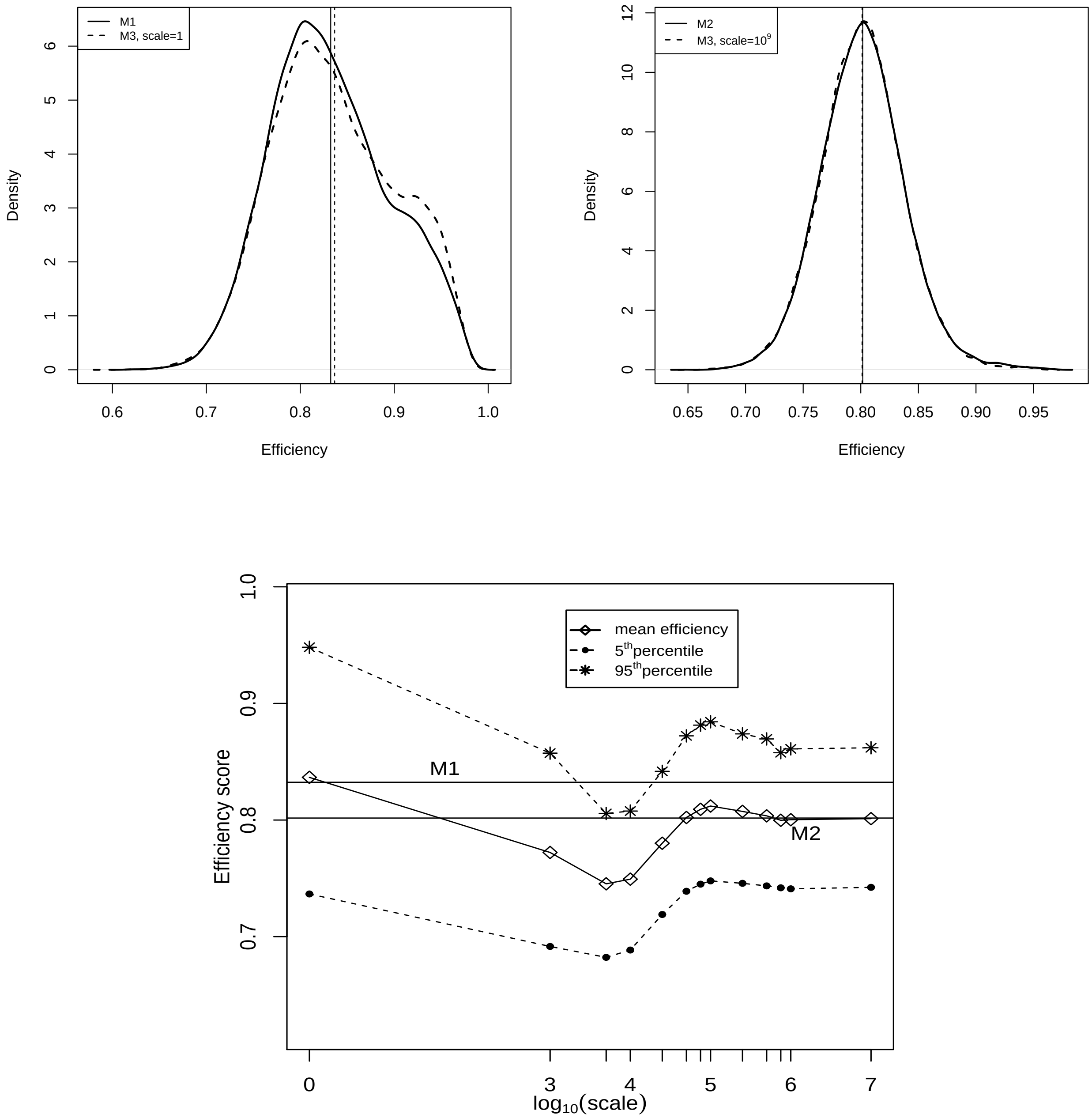

Figure 7.55: Turkey - Model Convergence, Efficiency Score.

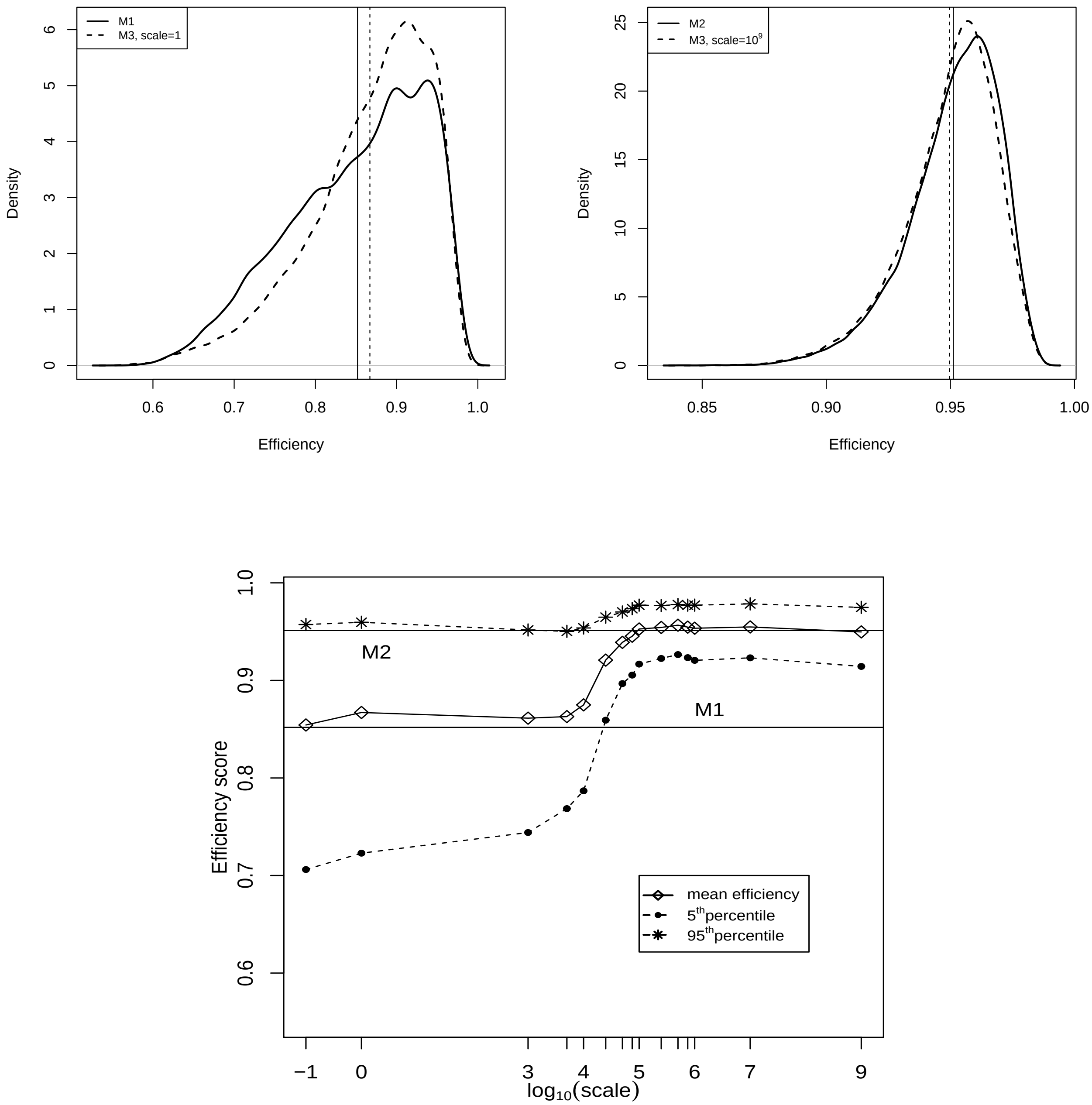

Figure 7.56: United Kingdom - Model Convergence, Efficiency Score.

7.4.3 σ^2

Figures 7.57 through 7.70 illustrate the hybrid model's convergence in distribution and mean to M1 and M2 and capture the convergence patterns as they trace the mean of σ^2 for each country with the variation of the prior scale.

As in the previous cases, we can observe that the posterior marginal densities for σ^2 obtained from the individual country frontier (M1) overlap almost exactly for all the countries with the posterior marginal densities obtained with the multi-country hybrid model and a weak prior (M3 with small scale factor). This allows us to conclude that with a weak prior, model M3 converges to model M1.

The posterior marginal densities for σ^2 derived under the common frontier assumption (M2) are virtually identical for all countries with the posterior marginal densities derived with the multi-country hybrid model when using a strong prior (M3 with big values for the scale factor). We can therefore conclude that model M3 with a strong prior converges to model M2.

The convergence path is indirect for Turkey, Romania and Germany. For these countries it is also the case that the posterior mean of σ^2 does not change much between models. Because of the small range, it is more likely for them to get out of bounds. The biggest changes for σ^2 can be observed for Switzerland, Serbia and Italy. The increase in σ^2 especially for Switzerland and Italy as they have more observations might be interpreted as a sign that they could have separate frontiers.

In some cases (Italy, Romania, Serbia) we notice that the highest density regions get wider as the prior strength increases and we move from the single frontier to the common frontier.

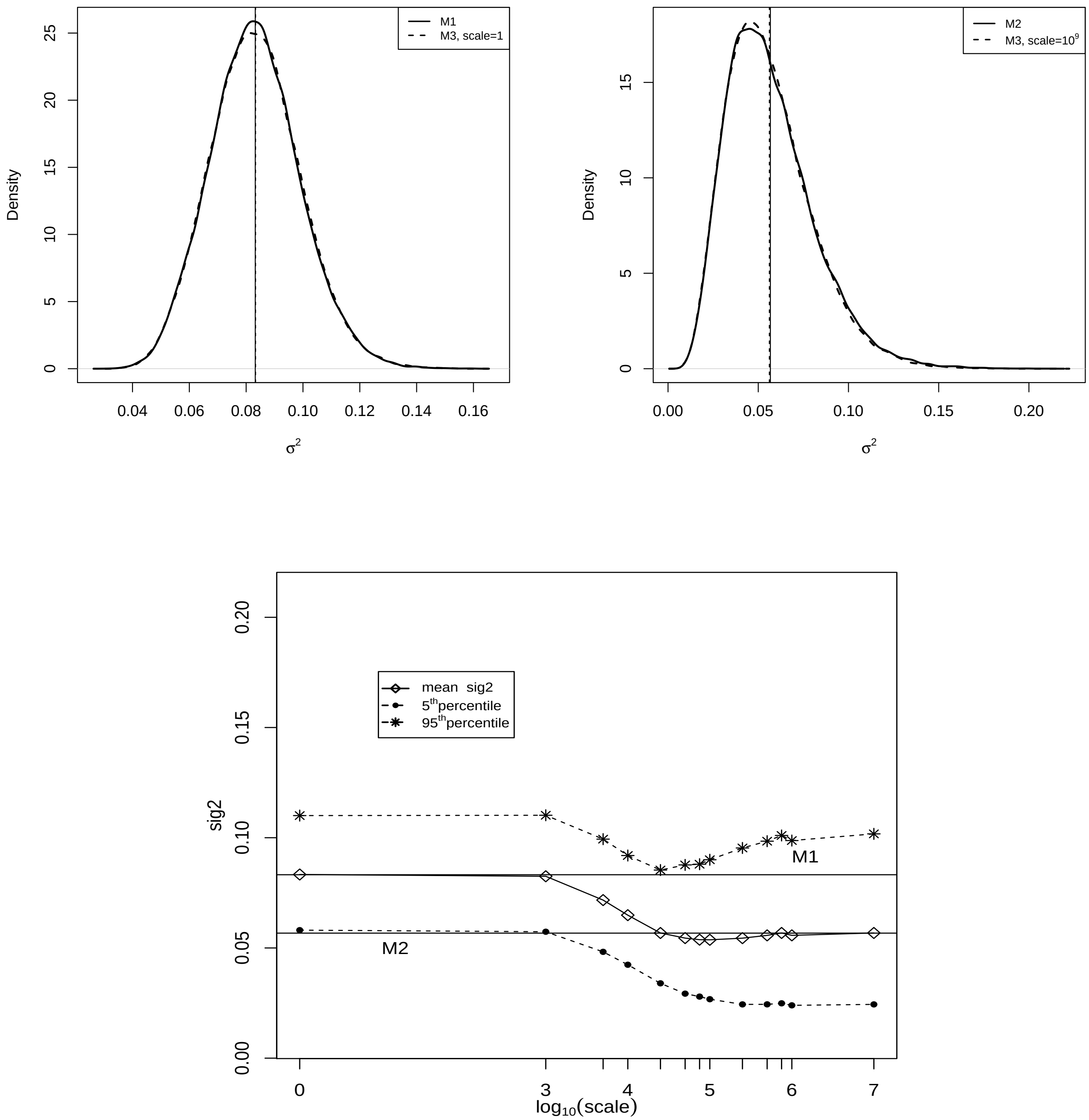

Figure 7.57: Croatia - Model Convergence, σ^2.

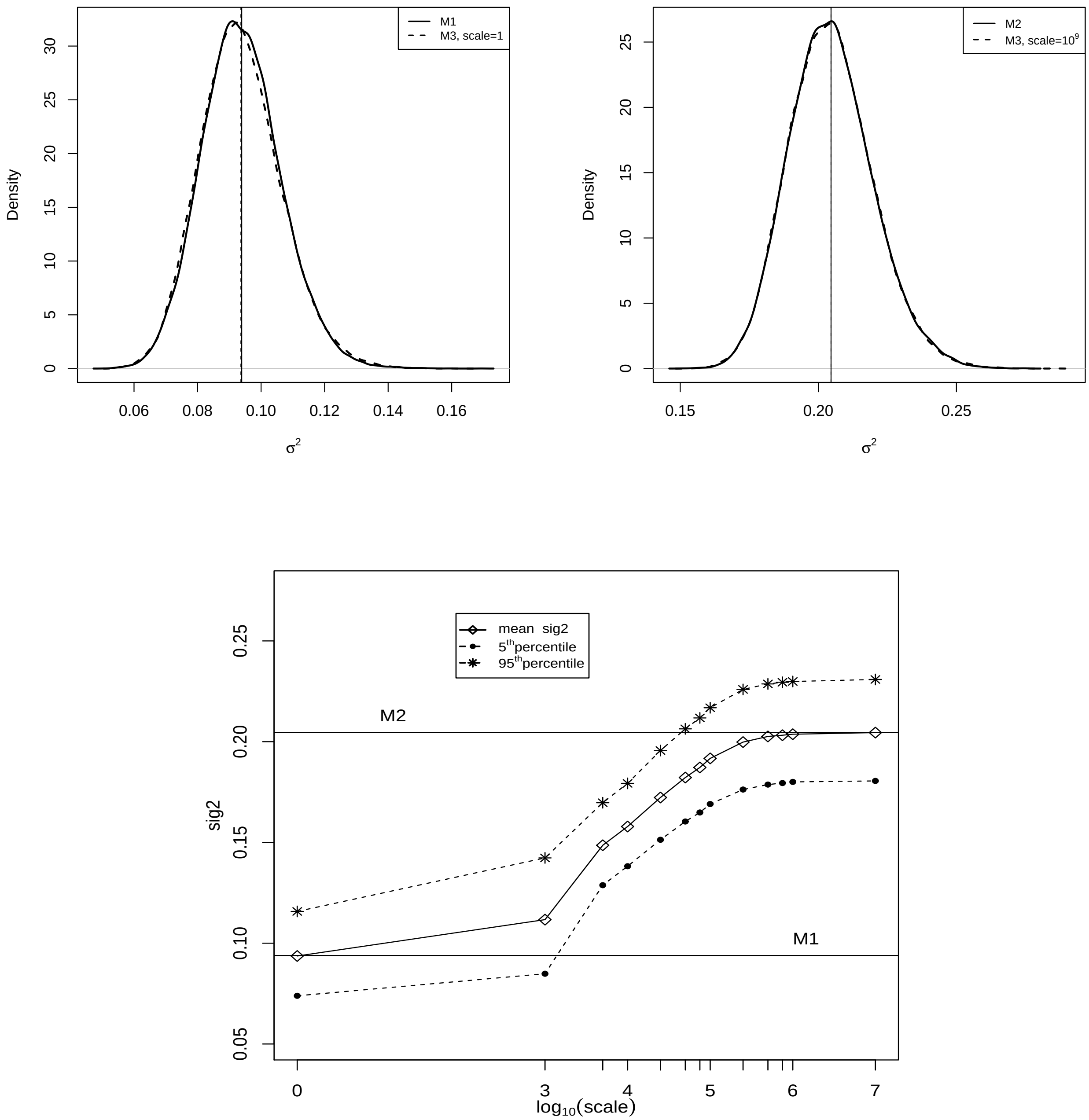

Figure 7.58: Denmark - Model Convergence, σ^2.

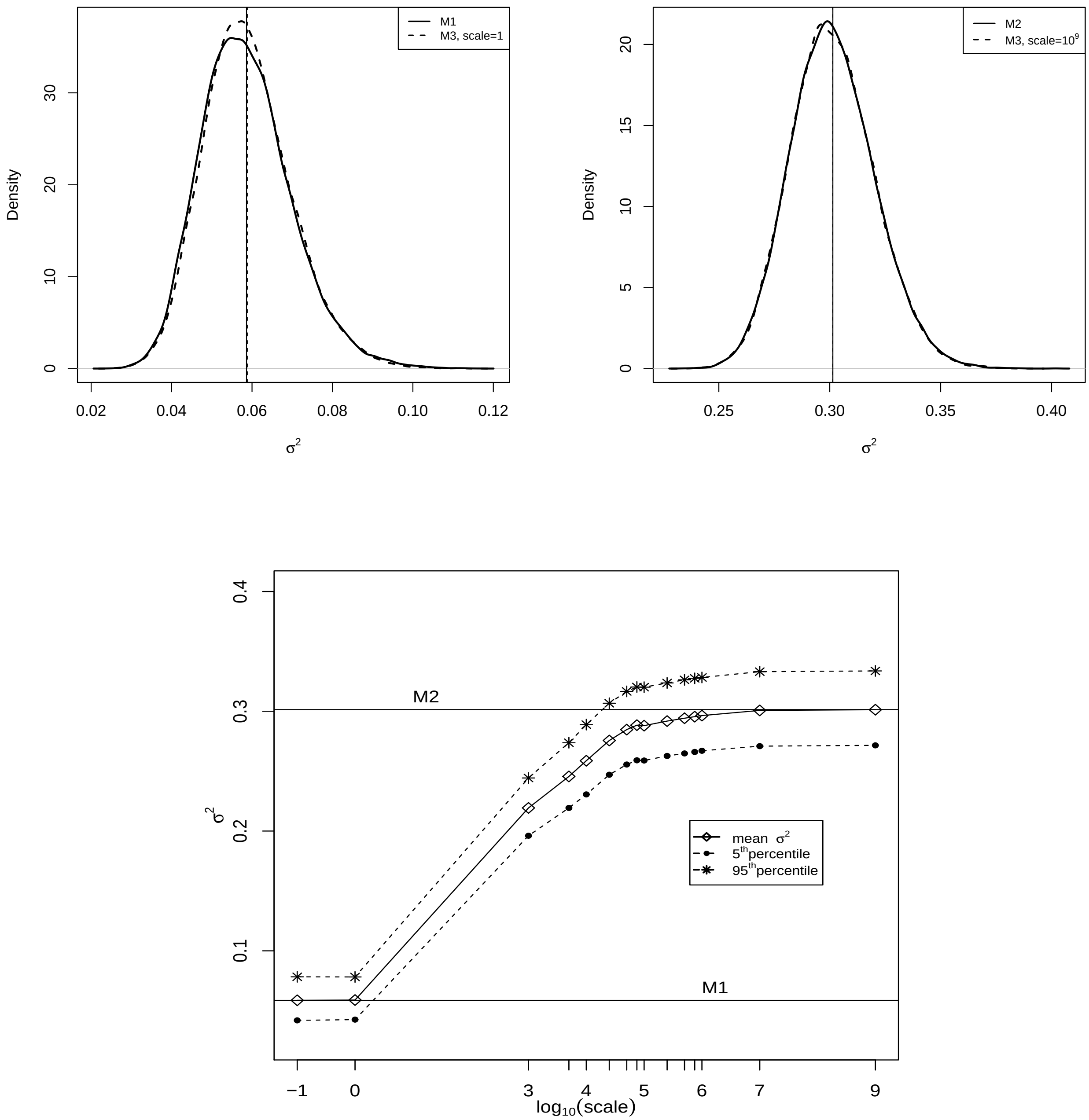

Figure 7.59: France - Model Convergence, σ^2.

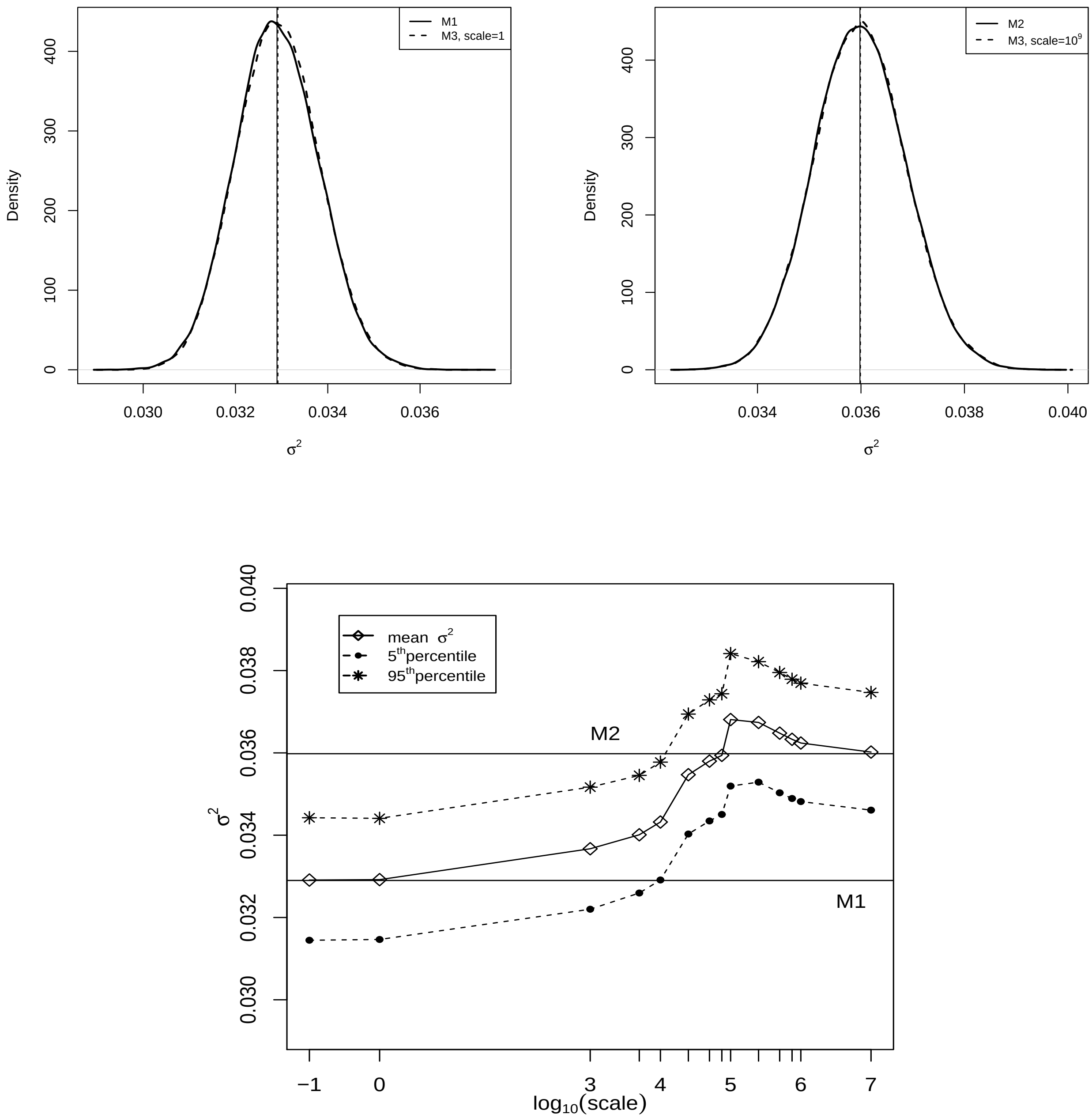

Figure 7.60: Germany - Model Convergence, σ^2.

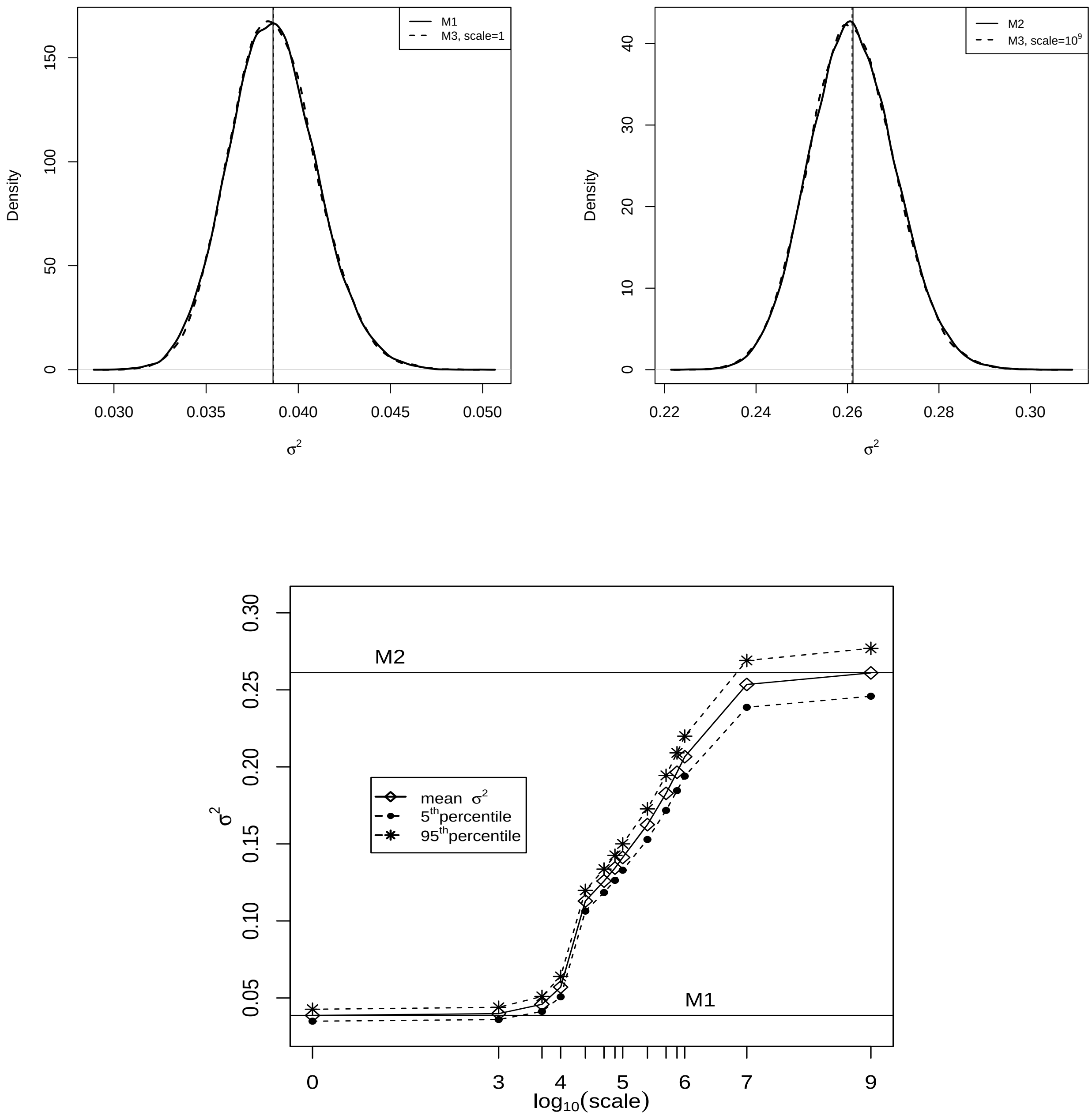

Figure 7.61: Italy - Model Convergence, σ^2.

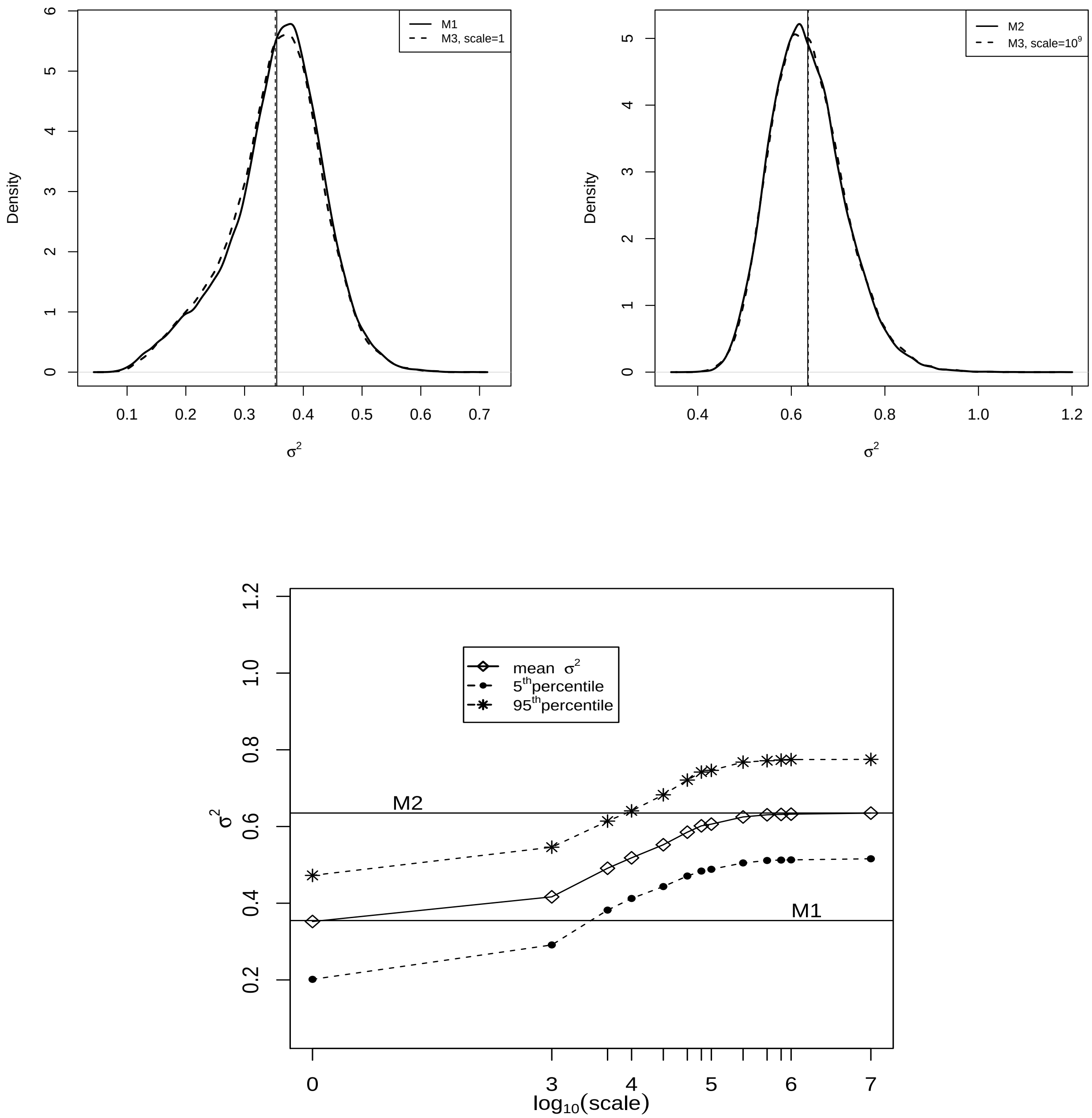

Figure 7.62: Netherlands - Model Convergence, σ^2.

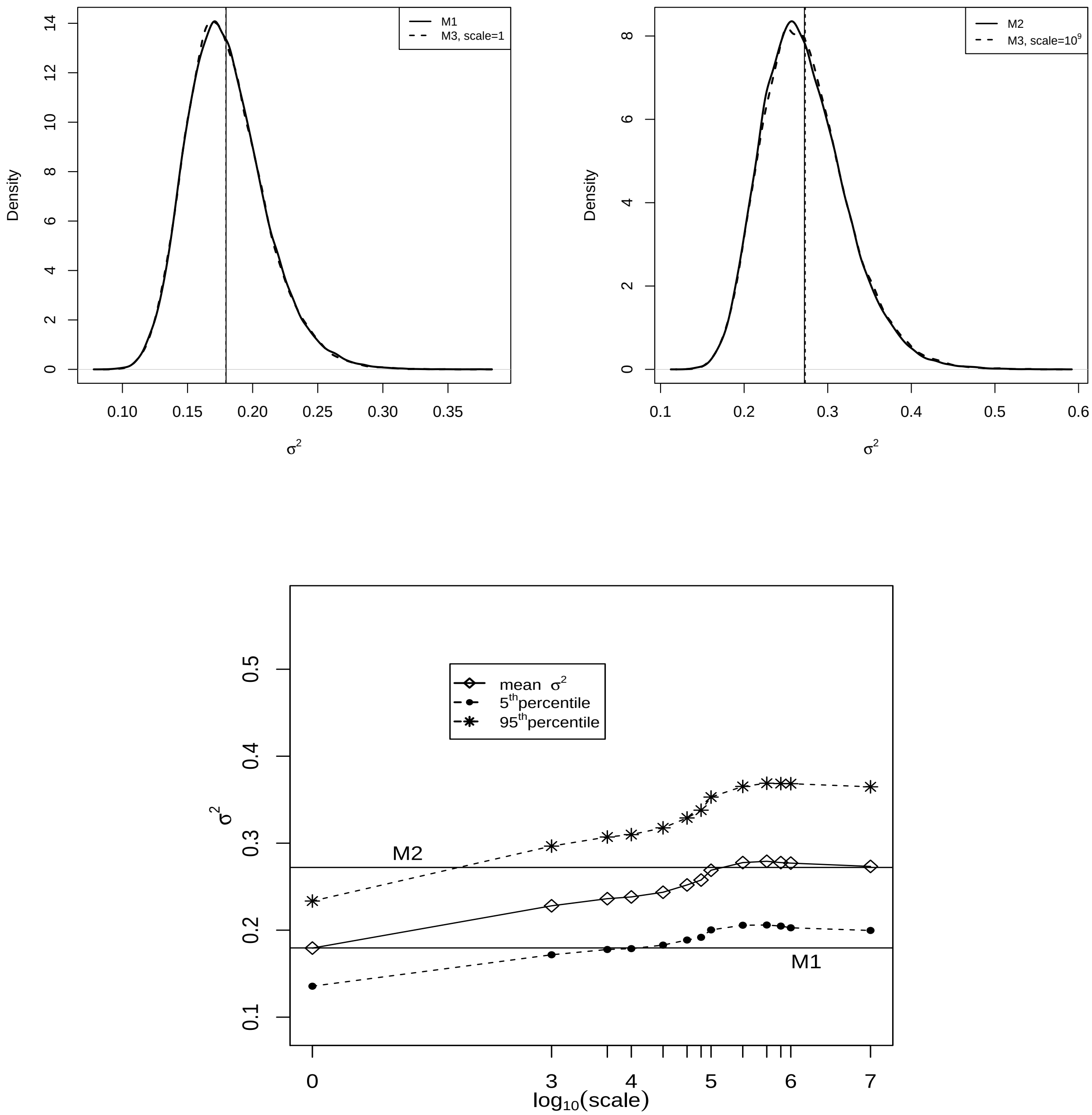

Figure 7.63: Poland - Model Convergence, σ^2.

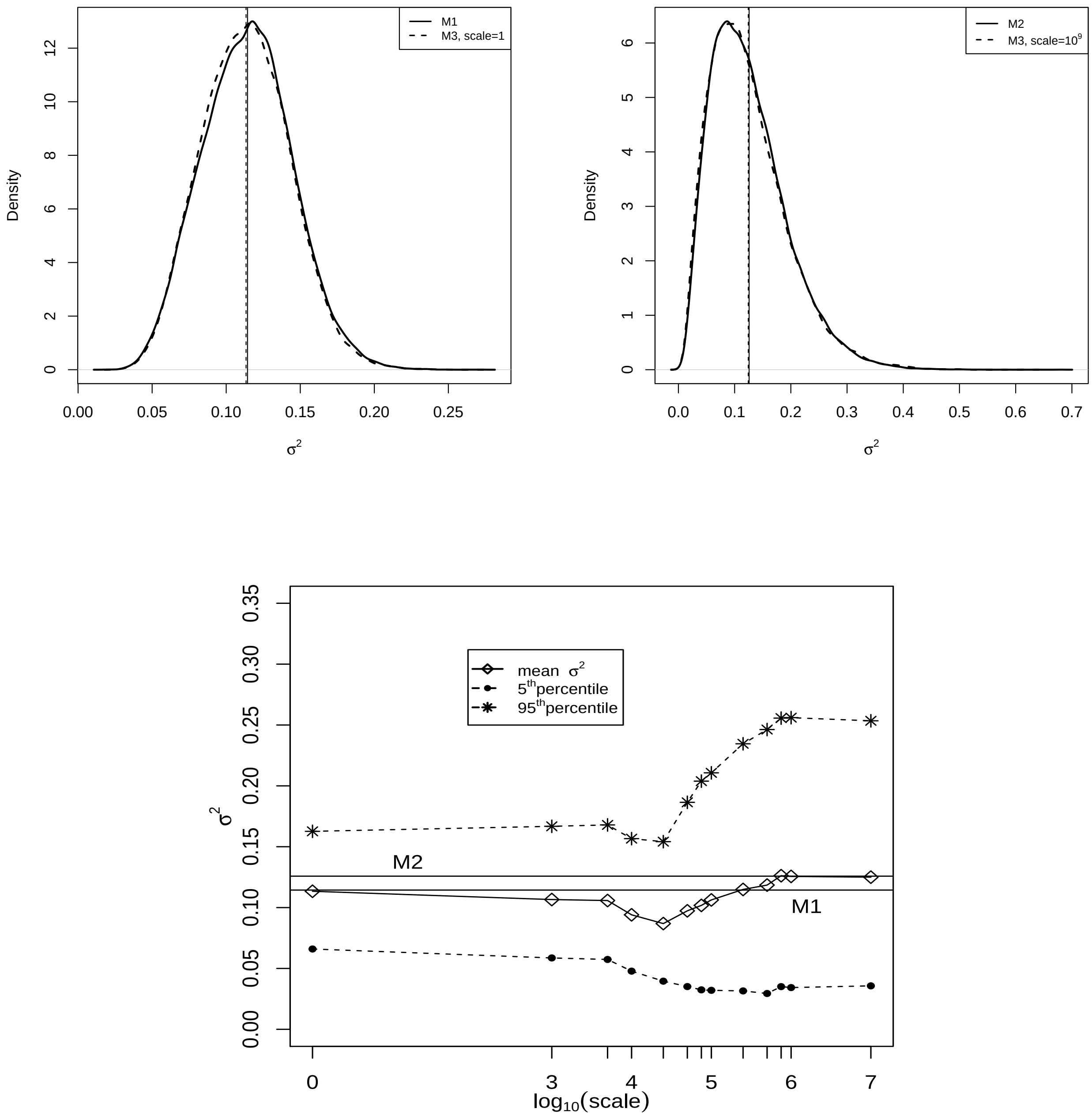

Figure 7.64: Romania - Model Convergence, σ^2.

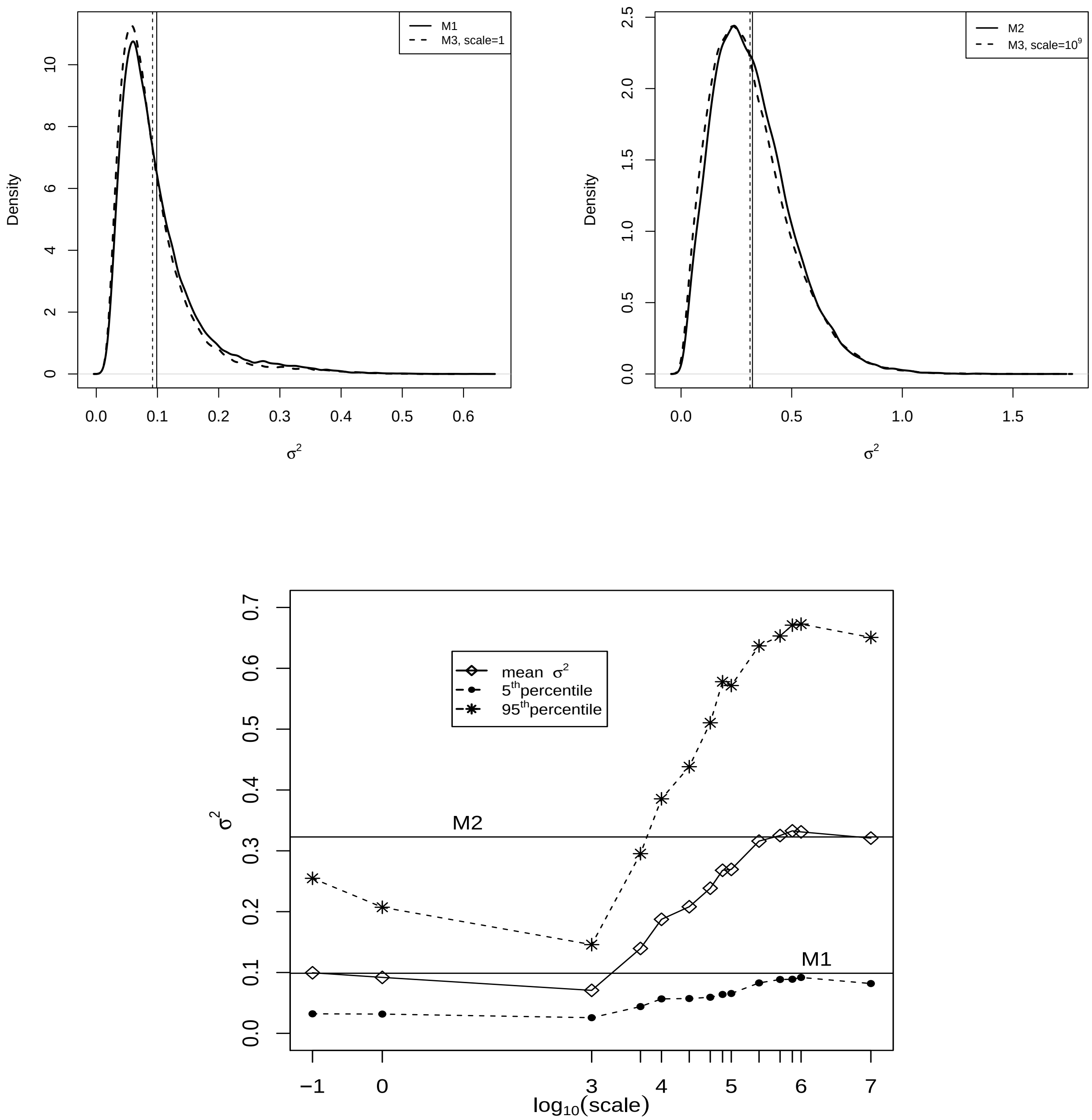

Figure 7.65: Serbia - Model Convergence, σ^2.

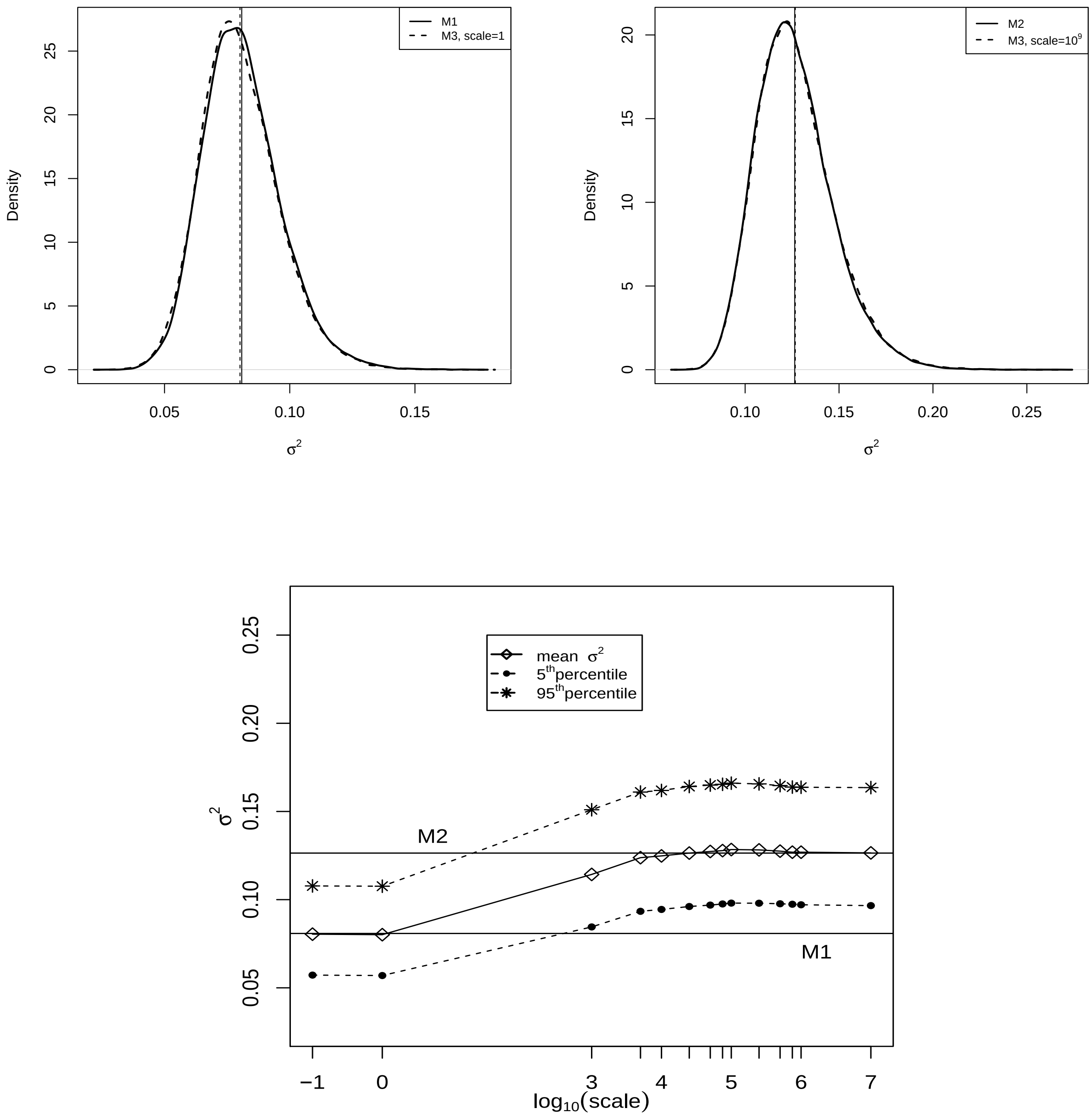

Figure 7.66: Slovenia - Model Convergence, σ^2.

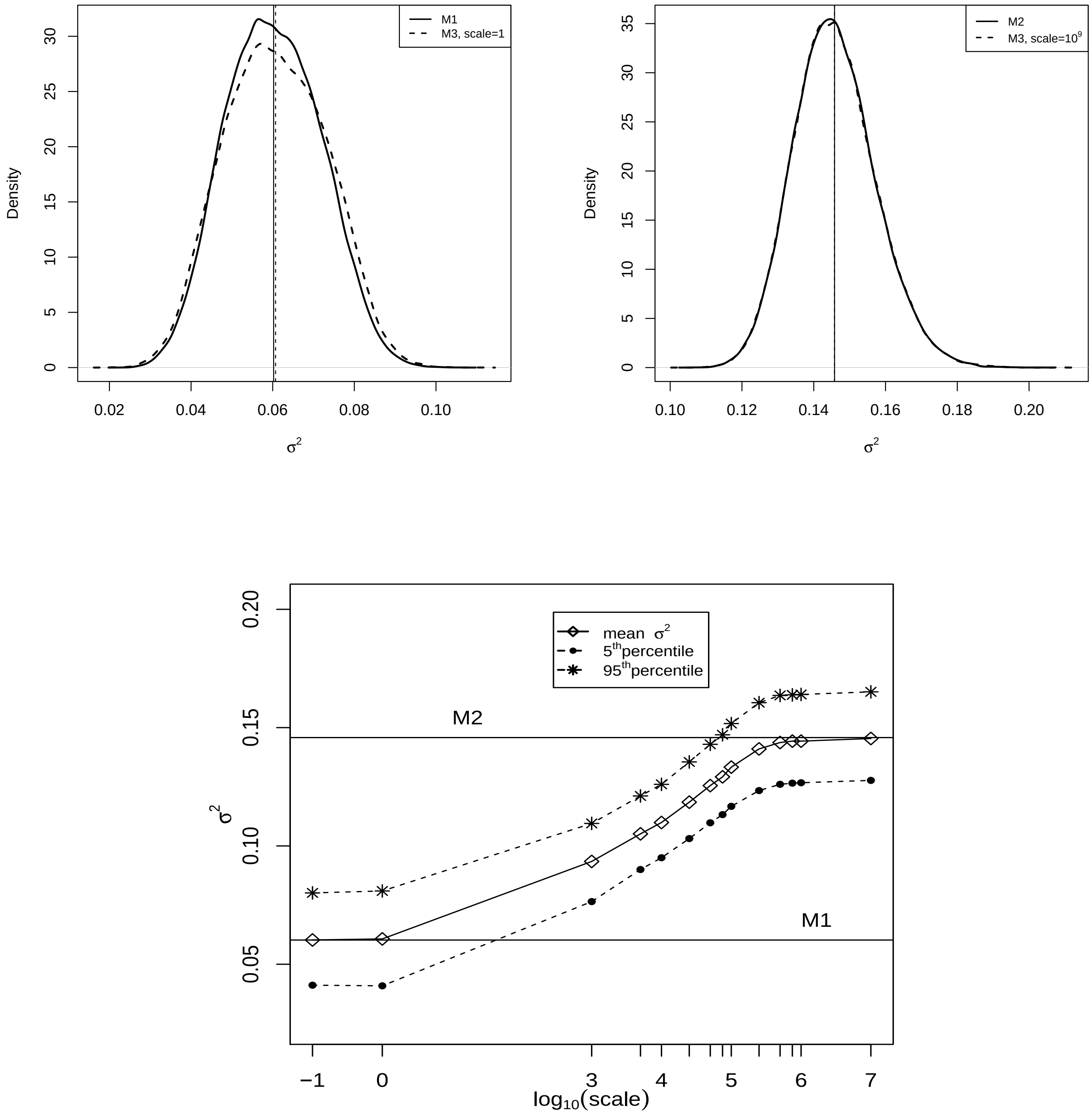

Figure 7.67: Sweden - Model Convergence, σ^2.

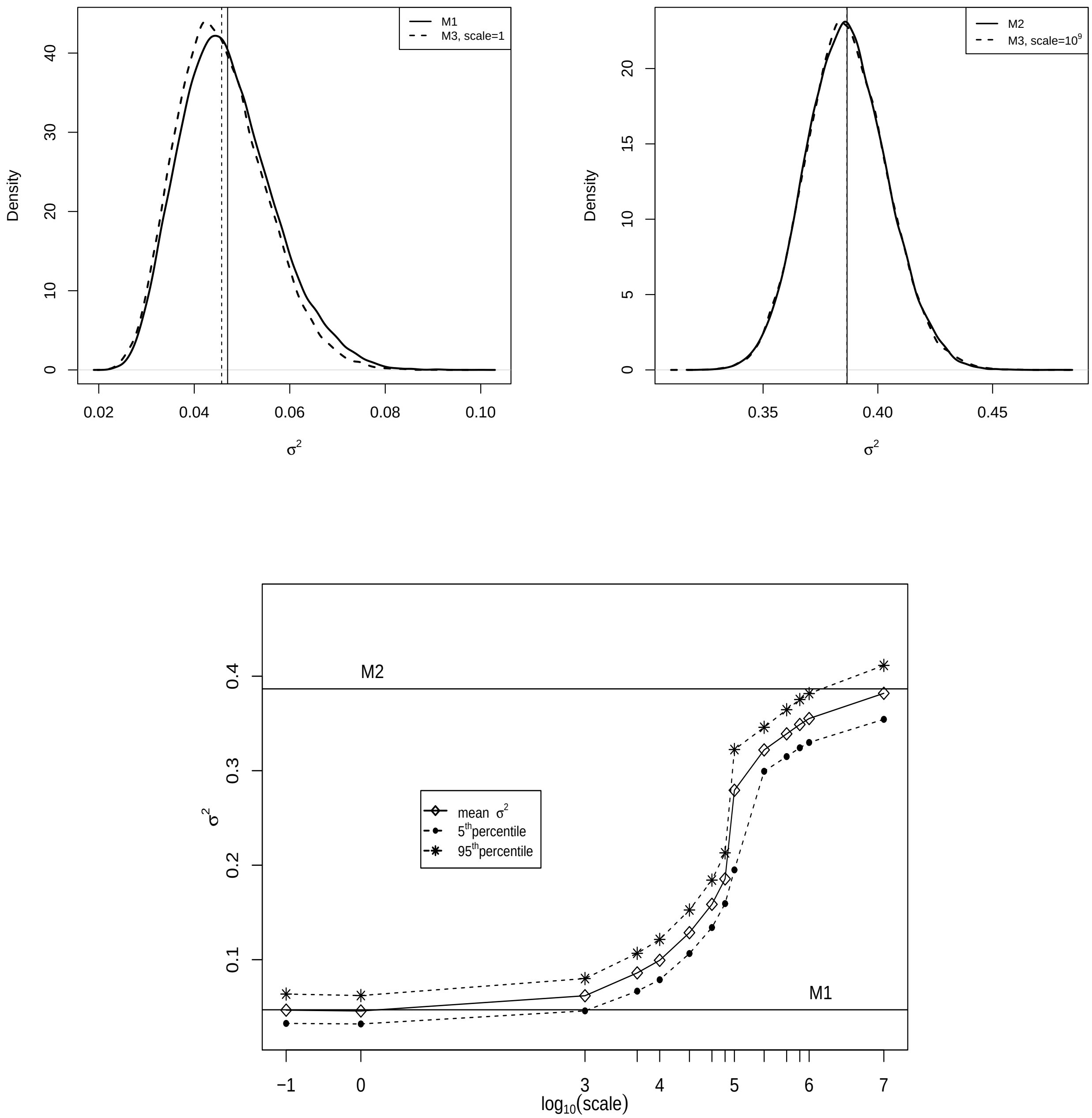

Figure 7.68: Switzerland - Model Convergence, σ^2.

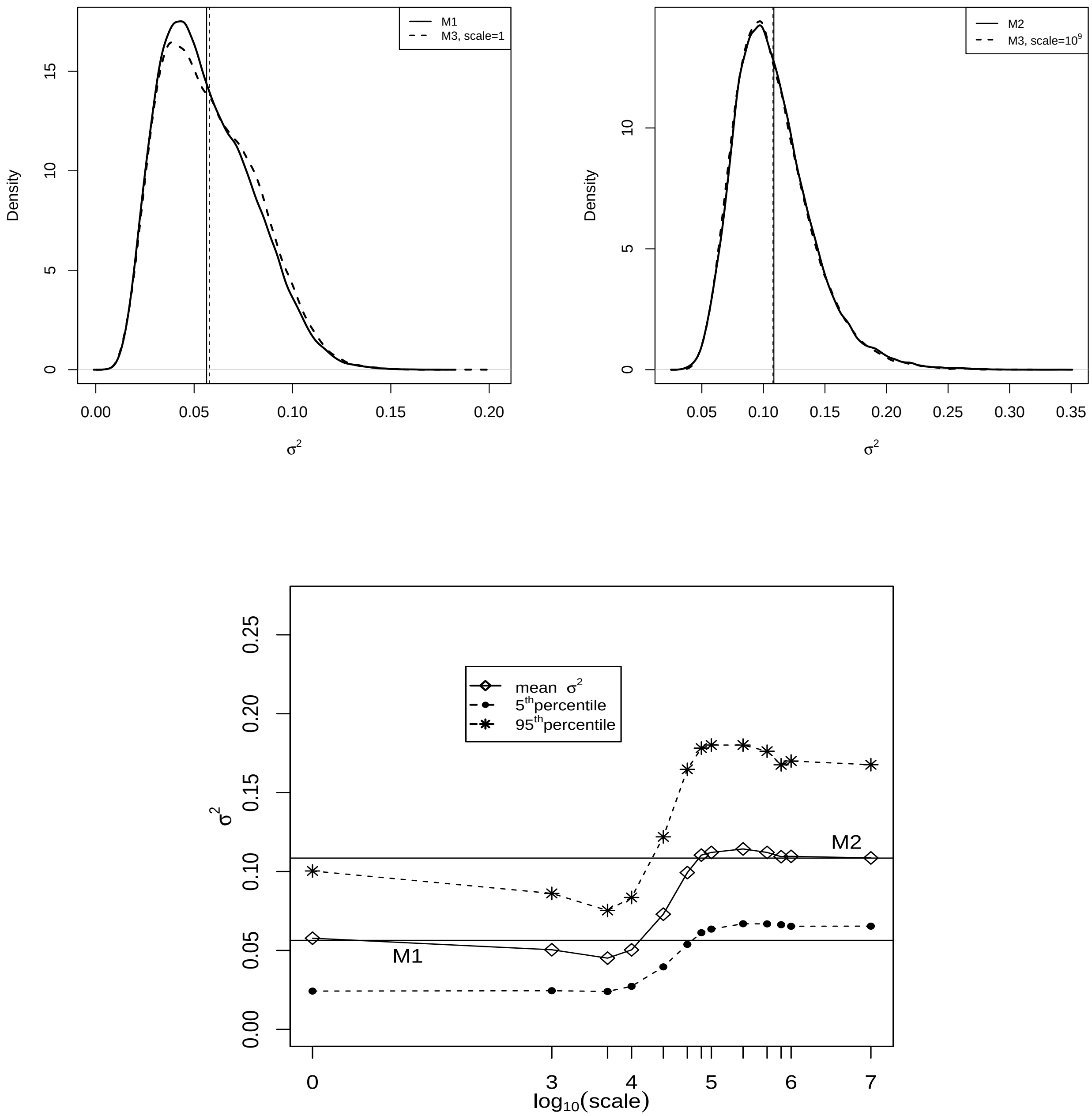

Figure 7.69: Turkey - Model Convergence, σ^2.

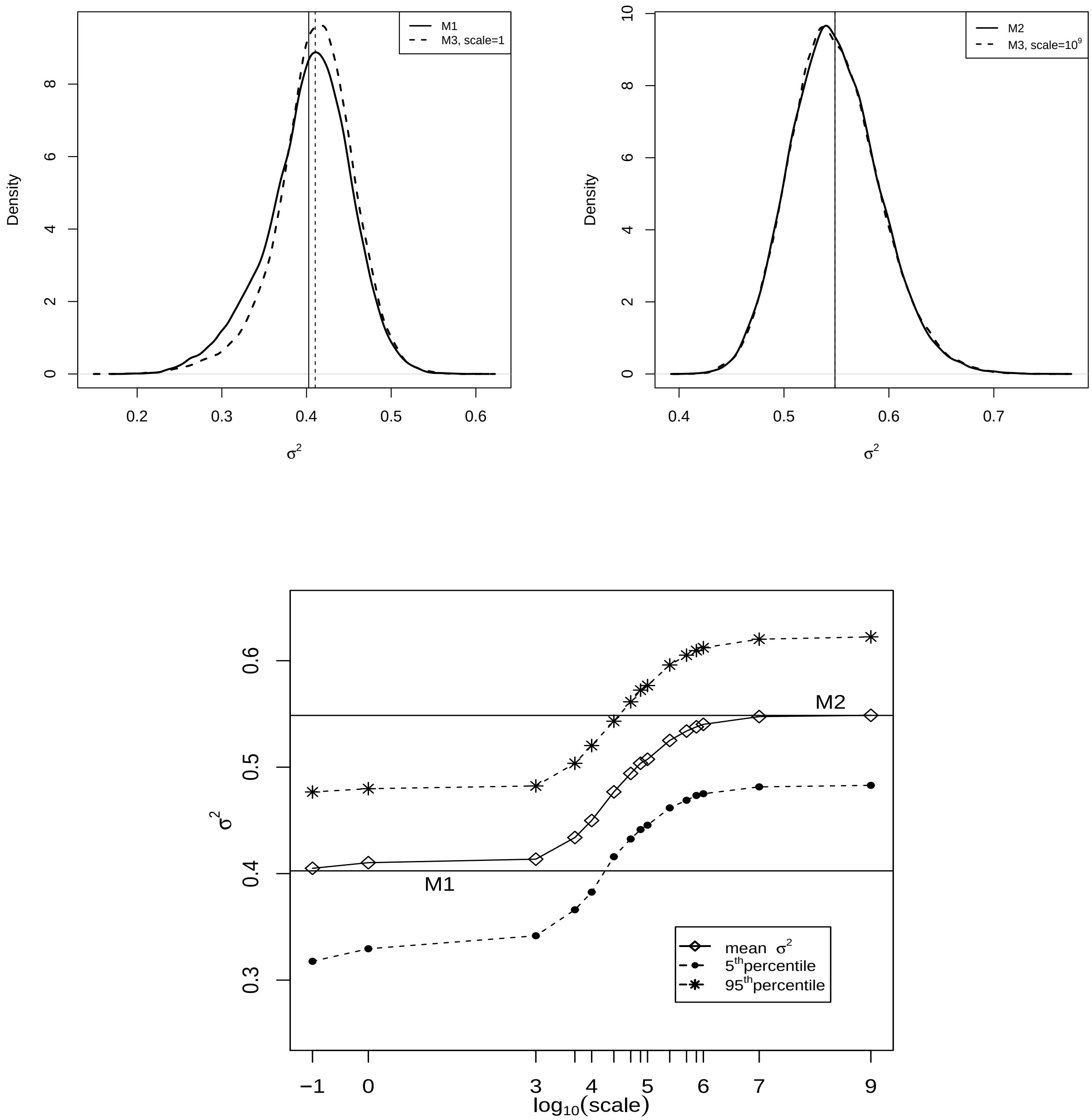

Figure 7.70: United Kingdom - Model Convergence, σ^2.

7.5 Conclusions

In this chapter we implement a hybrid model that allows us to shift continuously from the individual cost frontiers of model M1 to the common cost frontier of model M2. Starting with the stochastic cost frontier model from chapter 6, we add country dummy variables to it and by varying the strength of the prior on the model's parameters, we are able to replicate the results from the previous two chapters.

With an uninformative prior on the variance of the translog parameters, the hybrid model generates the same results as M1. With a strong prior on the variance of the translog parameters, the hybrid model generates the same results as M2. In other words, the hybrid model is nesting both of the previous approaches (individual and common frontiers) and depending on how strong our belief is in favor of one approach or the other, we can accordingly change our prior and obtain the desired results. To illustrate the convergence, we look at posterior marginal densities for the translog parameters, economies of scale for select large banks from each country, λ, efficiency score and σ^2.

The convergence from M1 to M2 is direct more often than not, but there are situations when as the prior gets more informative (and we are moving from individual frontiers to a common frontier), the results go out of the bounds defined by M1 and M2. We find that this happens especially when the difference between the 2 models is very small in terms of parameters' values. Also, we observe situations in which it takes a very strong prior for the parameters' results to start adjusting and move from their M1 to their M2 values. This slow convergence can be seen as evidence coming from the data against the idea of a common frontier.

Chapter 8
Summary of Conclusions and Future Research

This dissertation was motivated primarily by Allen Berger's 2007 article on banking efficiency comparisons. Among the numerous studies that have explored this subject, two competing approaches that have often produced contradictory results stand out. They differ with respect to the way frontiers are constructed and relative efficiencies determined. These two empirical groups are either developing nation-specific frontiers or assuming a common frontier that may be used to determine and compare efficiencies across countries. There are drawbacks associated with each method.

The objective of this study is to present a Bayesian methodology that nests both of these approaches. We build up towards the hybrid, more general model, by first analyzing the cost efficiency of banks from 14 European countries against nation-specific frontiers (chapter 5), followed by the common frontier approach (chapter 6).

The technology differs significantly depending on our approach. Plots of the cost frontiers and posterior marginal densities of the translog parameters show for the common frontier that the technology is affected by the heterogeneity assumption (M2 versus M1 pooled) and is not exclusively driven by Germany as the country with the most observations.

The individual country frontiers appear to be quite different suggesting different technologies. Results also indicated that the cost function properties of monotonicity and concavity in input prices are violated for many frontiers.

For a group of selected banks, we compute economies of scale and while the results vary in magnitude depending on the approach, we find more often than not and for all bank sizes that they remain greater than one. Therefore, we can conclude that banks are not operating at their optimum level and could reduce average costs by increasing their output. The subject of economies of scale has been a source of argument for a long time as researchers have found contradictory results over the years. Mester (2010) pointed out that while estimations based on older datasets (from 1980's)[1] tend to find diseconomies of scale especially for the large banks, more recent datasets suggest that even large banks have economies of scale greater than one. This study supports these findings.

The small number of studies that investigate the efficiency of the Eastern European banking sectors, especially in comparison with their more developed Western counterparts was another incentive to pursue this topic.

We found differences between the country specific efficiency levels and common frontier estimations that are especially high in the case of the less developed countries from the former Easter European block (Serbia, Romania, Croatia). In the case of Switzerland, we find a much higher posterior mean efficiency score when assuming a common frontier than we found by developing a Swiss frontier.

The last model presented in this thesis is a flexible solution that nests both of these approaches (individual and common frontier). It has the advantage that through the use of an informative prior varied according to our beliefs about the frontiers, it allows for different "sub-frontiers" to exist.

[1] "For years the Federal Reserve had been concerned about the ever larger size of our financial institutions. Federal Reserve research had been unable to find economies of scale in banking beyond a modest-sized institution"(from Greenspan, 2010).

With an uninformative prior on the variance of the translog parameters, the hybrid model generates the nation-specific frontier results. With a strong prior on the variance of the translog parameters, the hybrid model reproduces the same results as the common frontier approach.

We also find that as the strength of the prior increases and we move from single frontiers for each country towards a common "European frontier", the convergence does not always happen in a direct manner.

The fact that in some cases we need a very strong prior for the parameters' results to start adjusting and move from their single frontier values to their common frontier values might be interpreted as evidence from the data against the idea of a common frontier.

The complexity of the convergence process suggests that our analysis could be improved in future research by exploring the idea of Bayesian model averaging (BMA)[2]. A natural follow-up would be to investigate[3], at least in the case of the countries with more observations if the efficiency levels changed over time by assuming time varying technical efficiency.

Another avenue for future research is to incorporate monotonicity and concavity conditions[4].

[2]see Hoeting et al., 1999.
[3]using Ghadge and Ramanathan (2012)
[4]see Terrell(1996) and McCausland(2008).

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Appendix 1 Gibbs Sampler for the Single Frontier Model

We start with the basic stochastic frontier model:

$$\ln(c_i) = f(p_i, q_i) + v_i + u_i,$$

where c_i is the total observed cost of firm i, while $f(p_i, q_i)$ represents the cost frontier of the efficient firm that faces a set of input prices (p_i) and produces certain levels of output (q_i).

A firm's deviation from the cost frontier $(f(p_i, q_i))$ is given by $u_i + v_i$, where u_i is the statistical noise (the symmetric error) and v_i is the inefficiency (non-negative) for firm i.

A measure of the firm's specific efficiency (r_i) is calculated using the minimum cost attainable in the environment characterized by the random shocks u_i and the observed cost for firm i as follows:[5]

$$\text{CE}_i = \frac{\exp\left[f(p_i, q_i)\right]\exp\left(u_i\right)}{c_i} = \exp\left(-v_i\right) = r_i$$

.

For the cost function we choose a translog functional form, having the following general format:

$$\begin{aligned} f(p,q) = \ln[c(p,q)] = a_0 &+ \sum_{j=1}^{2} a_j \ln(q_j) + \sum_{k=1}^{2} b_k \ln(p_k) + \frac{1}{2}\sum_{j=1}^{2}\sum_{k=1}^{2} a_{jk}\ln(q_j)\ln(q_k) \\ &+ \frac{1}{2}\sum_{j=1}^{2}\sum_{k=1}^{2} b_{jk}\ln(p_j)\ln(p_k) + \sum_{j=1}^{2}\sum_{k=1}^{2} c_{jk}\ln(q_j)\ln(p_k) \end{aligned}$$

where $a_{jk} = a_{kj}$ for all $j, k = 1, 2$, $\sum_{k=1}^{2} b_k = 1$, $\sum_{k=1}^{2} b_{jk} = 0$, and $\sum_{k=1}^{2} c_{jk} = 0$.

[5] following Kumbhakar and Lovell (2003).

Using banking data, we construct[6] the variables for the translog function. Banks are productive entities that are using labor and purchased funds to produce loans, deposits and other earning assets. The input prices in this case are the wage and the interest rates, while the outputs are loans and securities.

The price of labor (avwage) is an averaged value of the personnel expenses per employee, while the price of funds (avrate) is calculated as a ratio between the interest rate expenses and total deposits. We normalize the total cost, loans, and securities by equity and we scale the normalized total cost and the price of labor by the price of funds in order to guarantee the linear homogeneity of the cost function.

The above constructed variables are plugged into the translog cost function and we obtain the following formula:

$$
\begin{aligned}
\ln\left(\frac{\text{cost}}{\text{equity} \times \text{avrate}}\right) &= \beta_1 + \beta_2 \times \ln\left(\frac{\text{avwage}}{\text{avrate}}\right) + \beta_3 \times \left[\ln\left(\frac{\text{avwage}}{\text{avrate}}\right)\right]^2 \\
&+ \beta_4 \times \ln\left(\frac{\text{loan}}{\text{equity}}\right) + \beta_5 \times \left[\ln\left(\frac{\text{loan}}{\text{equity}}\right)\right]^2 \\
&+ \beta_6 \times \ln\left(\frac{\text{security}}{\text{equity}}\right) + \beta_7 \times \left[\ln\left(\frac{\text{security}}{\text{equity}}\right)\right]^2 \\
&+ \beta_8 \times \left[\ln\left(\frac{\text{avwage}}{\text{avrate}}\right)\right] \times \ln\left(\frac{\text{loan}}{\text{equity}}\right) \\
&+ \beta_9 \times \left[\ln\left(\frac{\text{avwage}}{\text{avrate}}\right)\right] \times \ln\left(\frac{\text{security}}{\text{equity}}\right) \\
&+ \beta_{10} \times \left[\ln\left(\frac{\text{loan}}{\text{equity}}\right)\right] \times \left[\ln\left(\frac{\text{security}}{\text{equity}}\right)\right] \\
&= \sum_{m=1}^{10} \beta_m \mathbf{x_{.m}}
\end{aligned}
$$

.

[6]following Lewis and Terrell(2011)

Therefore, we can define the following $N \times 1$ vectors, with N=number of observations:

$$\mathbf{x_{.1}} = (x_{11}, x_{21}, ..., x_{N1})^T = (1, 1, ..., 1)^T$$
$$\mathbf{x_{.2}} = (x_{12}, x_{22}, ..., x_{N2})^T = \ln\left(\frac{\text{avwage}}{\text{avrate}}\right)$$
$$\mathbf{x_{.3}} = (x_{13}, x_{23}, ..., x_{N3})^T = \left[\ln\left(\frac{\text{avwage}}{\text{avrate}}\right)\right]^2$$
$$\mathbf{x_{.4}} = (x_{14}, x_{24}, ..., x_{N4})^T = \ln\left(\frac{\text{loan}}{\text{equity}}\right)$$
$$\mathbf{x_{.5}} = (x_{15}, x_{25}, ..., x_{N5})^T = \left[\ln\left(\frac{\text{loan}}{\text{equity}}\right)\right]^2$$
$$\mathbf{x_{.6}} = (x_{16}, x_{26}, ..., x_{N6})^T = \ln\left(\frac{\text{security}}{\text{equity}}\right)$$
$$\mathbf{x_{.7}} = (x_{17}, x_{27}, ..., x_{N7})^T = \left[\ln\left(\frac{\text{security}}{\text{equity}}\right)\right]^2$$
$$\mathbf{x_{.8}} = (x_{18}, x_{28}, ..., x_{N8})^T = \ln\left(\frac{\text{avwage}}{\text{avrate}}\right) \times \ln\left(\frac{\text{loan}}{\text{equity}}\right)$$
$$\mathbf{x_{.9}} = (x_{19}, x_{29}, ..., x_{N9})^T = \ln\left(\frac{\text{avwage}}{\text{avrate}}\right) \times \ln\left(\frac{\text{security}}{\text{equity}}\right)$$
$$\mathbf{x_{.10}} = (x_{1,10}, x_{2,10}, ..., x_{N,10})^T = \ln\left(\frac{\text{loan}}{\text{equity}}\right) \times \ln\left(\frac{\text{security}}{\text{equity}}\right).$$

In general, we have $\mathbf{x_{.m}} = (x_{1m}, x_{2m}, ..., x_{Nm})^T$, the $N \times 1$ column vector that represents the mth translog variable, where $m = 1, ..., 10$, and N=number of observations.

We also write the dependent variable as a $N \times 1$ vector:

$$\mathbf{y} = (y_1, ..., y_N)^T = \ln\left(\frac{\text{cost}}{\text{equity}\times\text{avrate}}\right).$$

In order to rewrite the model in a simplified mode using matrix algebra, we need to define:

- $\boldsymbol{\beta} = (\beta_1, \beta_2, ..., \beta_{10})^T$ as the 10×1 column vector of the translog coefficients that characterizes the technology of the frontier.
- $\mathbf{x_{i.}} = (x_{i1}, x_{i2}, ..., x_{i10})$ as the 1×10 row vector of the translog variables written for each observation $i = 1, ..., N$.

We now have a linear composed error model for which we assume that the inefficiency term follows an exponential distribution while the statistical noise is normally distributed.

$$\begin{cases} y_i = \mathbf{x}_{i.}\boldsymbol{\beta} + v_i + u_i \\ v_i \sim EXP(\lambda) \\ u_i \sim N(0, \sigma_u^2) \end{cases}$$

where i refers to the bank i, with $i = 1, ..., N$.

The independent variables can now be grouped in a $N \times 10$ matrix:

$$\mathrm{X} = (x_{nm})_{\substack{n=1,\dots,N \\ m=1,\dots,M}} = \begin{pmatrix} x_{11} & x_{12} & \cdots & x_{1,10} \\ \vdots & \vdots & \ddots & \vdots \\ x_{i2} & x_{i2} & \cdots & x_{i,10} \\ \vdots & \vdots & \ddots & \vdots \\ x_{N1} & x_{N2} & \cdots & x_{N,10} \end{pmatrix}_{(N\times 10)} .$$

Given the model's assumptions, $\exp(-v_i) = r_i$ is the measure of bank i^{th}' efficiency, while $\mathbf{v} = (v_1, ..., v_N)^T$ is the $N\times1$ column vector of inefficiencies for all banks and $\mathbf{u} = (u_1, ..., u_N)^T$ is the $N \times 1$ column vector of random shocks.

Using the above notations, the model can be rewritten in vector notation and simplified to the common linear regression model:

$$\mathbf{y} - \mathbf{v} = \mathbf{y}^* = \mathrm{X}\boldsymbol{\beta} + \mathbf{u}$$

,

with $\mathbf{u} \sim \mathrm{N}(0, \sigma_u^2 \mathrm{I}_N)$, where I_N is the $N \times N$ identity matrix and $\mathbf{y}^* = ({y_1}^*, ..., {y_N}^*)^T$, ${y_i}^* = y_i - v_i$ for $i = 1, ..., N$.

The parameter vector of interest is now $\boldsymbol{\theta} = (\beta_1, \beta_2, ..., \beta_{10}, \sigma_u^2)$ and the "observations" y_i^* are conditionally independent given $\boldsymbol{\theta}$, X for all $i = 1, ..., N$.

Following the Gibbs algorithm described by Kleit and Terrell (1998) and using the conditional distributions derived by Koop, Osiewalski and Steel (1994) the procedure for a Bayesian estimation of a stochastic frontier model is broken down below in a stepwise manner:

Step 1: Choosing priors

1. A flat prior for $\boldsymbol{\beta}$: $\pi(\boldsymbol{\beta}) \propto 1$.

2. A gamma prior[7] for σ_u^{-2}: $\pi(\sigma_u^{-2}) = f_G(\sigma_u^{-2} | \frac{\tau}{2}, \frac{s_p^2}{2})$, where $f_G(.|\nu_1, \nu_2)$ is a gamma density[8] with mean ν_1/ν_2 and variance ν_1/ν_2^2.

   In order to place very little weight on the prior[9] for σ_u^{-2}, small values are chosen for the prior shape and location parameters: $\tau = 1$ and $s_p^2 = 0.10$. An arbitrary starting value is picked for the variance itself: e.g. $(\sigma_u^{-2})^{[0]} = 1$.

[7] following Fernandez, Osiewalski, and Steel (1997)

[8] for a random variable $X \sim \mathrm{GAM}(\nu_1, \nu_2)$, Bayesian texts and papers use the gamma density function written as: $f_G(x|\nu_1, \nu_2) = \frac{{\nu_2}^{\nu_1}}{\Gamma(\nu_1)} x^{\nu_1 - 1} \exp(-\nu_2 x)$.

[9] following Kleit and Terrell (2001)

3. Small, constant values are chosen as the starting point for the inefficiency parameters, e.g. $\mathbf{v}^{[0]} = [0.05 \ldots 0.05]^T{}_{(N\times 1)}$.

4. A gamma prior for λ^{-1}: $\pi(\lambda^{-1}) = f_G(\lambda^{-1}|1, -\ln(r^*))$, where r^* is the prior mean for efficiency. The initial value for the mean efficiency: $r^* = \exp(-\mathrm{v}^*) = 0.875$[10] is set to be the same for all countries and considering the number of observations in the samples, the results are not expected to be sensitive to the choice of r^*. Since $\lambda = \mathrm{E}[v_i] = v^*$, we have a starting value for λ: $\lambda^{[0]} = -\ln(r^*) \approx 0.13$

Step 2: Standard linear regression model - Bayesian approach

We focus on the following model:

$$\mathbf{y}^* = \mathrm{X}\boldsymbol{\beta} + \mathbf{u}$$

with the traditional two-sided error $\mathbf{u}$ being normally distributed, $\mathbf{u} \sim \mathrm{N}(0, \sigma_u^2 \mathrm{I}_N)$.

The joint posterior density of interest is now:

$$p(\boldsymbol{\theta}|\mathbf{y}^*) = p(\boldsymbol{\beta}, \sigma_u^2|\mathbf{y}^*).$$

The choice of a gamma prior[11] for σ_u^2 ensures the existence of a proper posterior[12] and taking into account the non-informative prior for $\underline{\beta}$, we have the following conditional densities from which we draw the parameters of interest:

1. conditional distribution of $\boldsymbol{\beta}$ given σ_u^2 and the "data" $(\mathbf{y}^*)$, $p(\boldsymbol{\beta}|\sigma_u^2, \mathbf{y}^*)$[13] is normal, $N(\widehat{\boldsymbol{\beta}}, \sigma_u^2 (X^T X)^{-1})$, where $\widehat{\boldsymbol{\beta}} = (X^T X)^{-1} X^T \mathbf{y}^*$, the OLS estimates for $\boldsymbol{\beta}$.

[10]following Koop, Osiewalski and Steel (1994) and van den Broek, Koop, Osiewalski and Steel (1994)

[11]following Kleit and Terrell (2001).

[12]While in many Bayesian stochastic frontier models a non-informative prior on both $\boldsymbol{\beta}$ and σ_u^2 is usually chosen: $\pi(\boldsymbol{\beta}, \sigma_u^2) \propto \frac{1}{\sigma_u^2}$, Fernandez, Osiewalski and Steel (1997) examine the existence of posterior distribution and moments under this assumption and find that in cross-sectional applications of this model it can lead to improper priors.

[13]for the simplified OLS model. The actual conditional distribution of interest is $p(\boldsymbol{\beta}|\sigma_u^2, \lambda, \mathbf{v}, \mathbf{y})$.

2. conditional distribution of σ_u^2 given $\boldsymbol{\beta}$ and the "data", $p(\sigma_u^2|\boldsymbol{\beta}, \mathbf{y}^*)$[14] is inverse gamma or, equivalently, the conditional distribution of the precision (reciprocal of variance, $\frac{1}{\sigma_u^2} = \sigma_u^{-2}$) is gamma: $p(\sigma_u^{-2}|\boldsymbol{\beta}, \mathbf{y}^*) = f_G(\sigma_u^{-2}|\frac{N+\tau-2}{2}, \frac{SSE+{s_p}^2}{2})$, where $SSE = \widehat{\mathbf{u}}^T\widehat{\mathbf{u}} = (\mathbf{y} - \mathbf{v} - X\widehat{\boldsymbol{\beta}})^T(\mathbf{y} - \mathbf{v} - X\widehat{\boldsymbol{\beta}})$.

Step 3: Inefficiencies

Using the conditional distributions for λ and $\mathbf{v}$ as derived by Koop, Osiewalski and Steel (1994), we sample them as follows:

1. The conditional distribution for the parameter of the one-sided error term will not be influenced by $\boldsymbol{\beta}$ or σ_u^2, it depends only on $\mathbf{v}$ and the gamma prior: $p(\lambda^{-1}|\boldsymbol{\beta}, \sigma_u^2, \mathbf{v}, \mathbf{y}) = f_G(\lambda^{-1}|N + 1, \mathbf{v}^T\mathbf{i}_N - \ln(r^*))$, where $\mathbf{i}_N$ is a $N \times 1$ vector of ones. Using the properties of the gamma distribution, we get the following formula for the inverse of the posterior mean efficiency $\mathrm{E}[\lambda^{-1}] = \frac{N+1}{\mathbf{v}^T\mathbf{i}_N - \ln(r^*)} = \frac{N+1}{\sum_{i=1}^N v_i - \ln(r^*)}$.
This means that for a large enough sample, the posterior mean of λ gets close to its maximum likelihood estimate given $\mathbf{v}$ which is equal to $\frac{\sum_{i=1}^N v_i}{N}$. The starting value for the mean efficiency (r^*) increases slightly the posterior mean for λ, but even for very low, unrealistic, average inefficiency levels (of 0.01 for example), the contribution of the prior is irrelevant to the results with sample sizes of 100 observations or more.

2. As derived by Jondrow et al. (1983), the conditional distribution of the inefficiency error for each firm (the vector $\mathbf{v}$), $p(\mathbf{v}|\boldsymbol{\beta}, \sigma_u^2, \lambda, \mathbf{y})$ is truncated normal: $TN(\mathbf{y} - X\widehat{\boldsymbol{\beta}} - \frac{\sigma_u^2}{\lambda}, \sigma_u^2 I_N)$, where TN is a normal probability distribution truncated below at zero and I_N is the $N \times N$ identity matrix.

[14] for the simplified OLS model. The actual conditional distribution of interest is $p(\sigma_u^{-2}|\boldsymbol{\beta}, \lambda, \mathbf{v}, \mathbf{y})$.

Since the conditional distribution for each parameter of interest is known and we can directly draw from them, the Gibbs sampler[15] for this problem is set up and the procedure is described below:

1. Choose starting values for the variance of the two-sided statistical disturbance, e.g. $(\sigma_u^2)^{[0]} = 1$ and the shape and location parameters of its prior distribution, $\tau = 1$ and $s_p^2 = 0.10$ (step 1.2).

2. Pick initial values for the inefficiency term $\mathbf{v}^{[0]}$ its mean $\lambda^{[0]}$ (steps 1.3 and 1.4).

3. Sample $\boldsymbol{\beta}^{[1]}$ given $\lambda^{[0]}$, $\mathbf{v}^{[0]}$, $(\sigma_u^2)^{[0]}$ and the data ($\mathbf{y}$): step 2.1.

4. Draw $(\sigma_u^2)^{[1]}$ conditional on $\lambda^{[0]}$, $\mathbf{v}^{[0]}$, $\boldsymbol{\beta}^{[1]}$ and the data ($\mathbf{y}$) using the conditional distribution from step 2.2.

5. Sample $\lambda^{[1]}$ given $\mathbf{v}^{[0]}$, the data ($\mathbf{y}$) and the updated parameters of the frontier, $\boldsymbol{\beta}^{[1]}$ and of the symmetrical error, $(\sigma_u^2)^{[1]}$ from the previous steps using the conditional distribution from step 3.1.

6. Sample $\mathbf{v}^{[1]}$ given $\lambda^{[1]}$, $\boldsymbol{\beta}^{[1]}$, $(\sigma_u^2)^{[1]}$ and the data, $\mathbf{y}$ (step 3.2).

7. Complete the posterior sample by repeating (3) through (6) while updating the parameters' initial values with the values obtained at the previous iteration.

Using the Gibbs sampling method with 55,000 iterations out of which we discard the first 5,000 to avoid sensitivity to the starting values, we generate a sample with 50,000 observations for each of the parameters of interest. As the number of iterations approaches infinity, the sampler converges to the actual joint density of the parameters, but considering the number of observations, the convergence is achieved relatively fast. 55,000 iterations prove to be sufficient, the convergence tests (Gelman-Rubin and Geweke diagnostics) giving satisfactory results.

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[15]following Koop, Steel and Osiewalski(1992)

Appendix 2 Economies of Scale

A measure for scale economies in our two output model is calculated for each bank following Caves, Christensen and Swanson (1981), based on the formula:

$\mathrm{ES}_j = (\sum_{i=1}^{2} \frac{\partial \ln(c(p_j,q_j))}{\partial \ln q_{ij}})^{-1}$, where $j = 1,..N$, N=number of observations for the country in question and i=1,2 the number of outputs.

$\sum_{i=1}^{2} \frac{\partial \ln(c(p_j,q_j))}{\partial \ln q_{ij}} = \beta_4 + 2\beta_5 \ln q_{1j} + (\beta_8+\beta_9)(\ln p_{1j} - \ln p_{2j}) + \beta_6 + 2\beta_7 \ln q_{2j} + \beta_{10}(\ln q_{1j} + \ln q_{2j})$

with $\ln q_{1j} = \ln(\text{loan/equity})_j = \mathrm{x_{j4}}$, $\ln q_{2j} = \ln(\text{security/equity})_j = \mathrm{x_{j6}}$

and $\ln p_{1j} = \ln(\text{avwage})_j$, $\ln p_{2j} = \ln(\text{avrate})_j \Rightarrow \ln p_{1j} - \ln p_{2j} = \mathrm{x_{j2}}$

The economies of scale are therefore a function of the model's parameters, input prices and output quantities:

$\mathrm{ES}_j = \frac{1}{\beta_4+\beta_6+(\beta_8+\beta_9)\mathrm{x_{j2}}+(2\beta_5+\beta_{10})\mathrm{x_{j4}}+(2\beta_7+\beta_{10})\mathrm{x_{j6}}}$

When drawing inferences about economies of scale ($\mathrm{ES}_j = f(\beta_4, \beta_5, \beta_6, \beta_7, \beta_8, \beta_9, \beta_{10})$) or other functions of interest (let's call them generically $g(\theta)$) that can be expressed as combination of the model's parameters (in our case $\theta = (\beta_4, \beta_5, \beta_6, \beta_7, \beta_8, \beta_9, \beta_{10})$), we use the sample from the posterior generated by the Gibbs sampler.

In general, if the posterior density of the parameters, $p(\theta)$, is known, the posterior means for any function of interest $g(\theta)$ are easy to compute as $\mathrm{E}[g(\theta)] = \int g(\theta)p(\theta)d\theta$. Nevertheless, since this integral cannot be computed analytically, we evaluate it numerically. By using the Gibbs algorithm, we sampled $n = 50,000$ values for each parameter θ_i from the posterior ($p(\theta)$) and the posterior mean for any function of interest can be calculated using the formula:

$\mathrm{E}[g(\theta)] = \frac{1}{n}\sum_{i=1}^{n} g(\theta_{\mathrm{i}})$.

Vita

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