Three Empirical Essays on the Determinants of Economic Growth

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0 Preface

Is there some action a government in India could take that would lead the Indian Economy to grow like Indonesia's or Egypt's? If so, what *exactly? If not, what is it about the "nature of India" that makes it so? The consequences for human welfare involved in questions like these are simply staggering: Once one starts to think about them, it is hard to think about anything else.*
-Robert E. Lucas, Jr. (1988, p.5)

Even if the recent growth experience suggests rephrasing the initial question to "What action did the Indian government take to transform the Indian economy into one of the fastest growing of the world?", the famous quote of Nobel laureate Robert E. Lucas is still as influential as it was 20 years ago. The fascination about economic growth emanates from the enormous implications that persistent differences in growth rates have for the prosperity of nations. Due to compounding effects even small differences in growth rates over longer periods of time have significant consequences on relative living standards. For instance, over the period 1870-1970 the average yearly growth rate of the Great Britain was 1.2 percent while that of Japan was 2.6 percent. In 1870 Japan's GDP per capita was less than one fourth of that of the leading industrialized country of that time. However, the cumulative effect of the relatively small growth advantage of Japan over Great Britain, led to a complete evaporation of the income gap by 1970.[1] But even during the recent decades we have observed substantial changes in the income relations. According to the latest version of the Penn World Tables the distribution of average yearly growth rates over the period 1960-2000 ranges from -1 percent for Madagascar to 6.3 percent for Taiwan. If not for missing data, the spread of growth rates would probably be even larger. Still, these differences had substantial implication for the standards of living. While Taiwan could increase its GDP per capita from $1443 in 1960 by a factor of 13 to $19,183 in 2000, Madagascar lowered its GDP per capita by a factor of 0.77 from

[1] The historical data are taken from the website of Agnus Maddison and can be downloaded at http://www.ggdc.net/maddison/.

$1267 in 1960 to $822 in 2000.[2] The experience of Taiwan and Madagascar can be seen as representative for a range of countries in East Asia and Sub-Saharan Africa, respectively. While East Asian countries started only slightly above African countries in the income distribution in 1960, many economies in East Asia managed to advance into the middle or even highest income group by 2000. In contrast, growth in Africa stagnated and these countries ended up by far the poorest in 2000. These stylized facts emphasize that to comprehend why countries differ dramatically in their prosperity, it is crucial to understand the determinants of long-term growth. "If we can learn about government policy options that have even small effects on long-term growth rates, we can contribute much (…) to the improvements of standards of living" (Barro and Sala-i-Martin, 2004, p.6).

This dissertation consists of three self-contained empirical essays. Each of the essays tries to make a moderate contribution to the understanding of the determinants of growth differences across countries. Chapter 1 focuses on the identification of growth determinants in high-income (OECD) countries, to understand the structures that drive the riches in industrialized countries that developing countries try to emulate.[3] Chapter 2 investigates the role of financial integration as a development strategy. It assesses under which conditions developing countries can expect to benefit from liberalizing their capital account. Chapter 3 analyzes the sources of Germany's departure from the technology frontier during the period 1991-2004. It employs a newly created industry-level database for Germany (see Röhn, Eicher and Strobel, 2007) to study the diverging labor productivity trends between Germany and the US.[4]

The underlying empirical framework in chapters 1 and 2 is the canonical cross country growth regression, which has become the workhorse for analyzing growth determinants following the influential contributions by Kormendi and Meguire (1985) and Barro (1991). In a pioneering study, Mankiw, Romer and Weil (1992) show how the neoclassical growth model of Solow (1956) can be transformed into a regression equation that is linear in observable variables. Their analysis uniquely

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[2] These income data are PPP adjusted in constant 2000 US Dollar from the Penn World Tables 6.2.
[3] This chapter is joined work with Theo Eicher and Chris Papageorgiou. See also Eicher, Papageorgiou, Röhn (2007).
[4] This chapter is joint work with Theo Eicher. See also Eicher, Röhn (2007).

shows how far even the neoclassical model can go in explaining heterogeneous growth experiences through differences in initial income, the population growth rate and the savings rates for (physical and human) capital. Inspired by the emergence of endogenous growth theories, many cross country regression studies have extended the Mankiw et al. framework by adding regressors that represent variables lying outside of Solow's original model to further our understanding of growth rate differences.[5] The distinction between the Solow variables and additional regressors is essential in understanding the modern empirical growth literature. While most empirical studies include the Solow variables along with growth determinants of interest, the choice of the usually small set of control variables varies greatly. This practice has generated a cornucopia of significant growth determinant and has led to skepticism about the robustness of these growth determinants as well as about cross country growth regressions in general.

Chapter 1 and 2 address this critique by explicitly accounting for *model uncertainty* using Bayesian Model Averaging (BMA) techniques. In general, *model uncertainty* acknowledges that in economic theory competing theories or models exist to explain the same phenomenon without consensus about the "correct" model. While the issue of *model uncertainty* is not unique to growth research it appears particularly troublesome for at least two reasons: First, as Brock and Durlauf (2001) argue modern growth theories are fundamentally *open-ended*, in that one growth theory does not logically preclude another. Moreover, the emergence of endogenous growth models has led to an abundance of plausible growth theories and an even greater number of variables to proxy for different aspects of these theories.[6] Second, the number of observations is typically small (usually less than 100 in a cross country study). This renders standard practices to empirically distinguish between the relevance of particular regressors, such as estimating the saturated model, impossible due to the lack of sufficient degrees of freedom. The array of possible growth determinants together with the limited number of observations has led researcher to emphasize a single or a small set of models and carry out inference as if this model repre-

[5] These additional variables can be understood as allowing for heterogeneity in either the steady state growth rate or the initial level of technology which Mankiw et al. (1992) treat as constant (see Durlauf, Johnson and Termple, 2005).
[6] Durlauf, Johnson and Temple (2005) count over 145 different growth regressors that have been found to be statistically significant in at least one study corresponding to 43 distinct growth theories.

sented the "true" data generating process. However, this practice understates the uncertainty that surrounds the validity of that model and led to the problem that different studies have drawn different conclusions depending for instance on the choice of control variables. In response, Bayesian Model Averaging (BMA) techniques, which treat the "true" growth model as an unknown, have been advocated. These techniques make probability statements about model parameters accounting for the probability that each model in a candidate model space is the correct one. They therefore incorporate the variance component associated the uncertainty about the correct model.[7]

Chapter 1 addresses in addition to model uncertainty a further important problem of cross sectional growth regression: *parameter heterogeneity*. The assumption of parameter homogeneity across countries has been criticized repeatedly (e.g. Temple 2000), since the assumption seems especially inappropriate when analyzing such heterogeneous and complex objects as countries (Brock and Durlauf, 2001). In Harberger's (1987, p. 256) famous words: "What do Thailand, the Dominican Republic, Zimbabwe, Greece, and Bolivia have in common that merits their being put in the same regression analysis?" In contrast to much of the previous literature that has focused on low income countries, chapter 1 studies the growth determinants of high-income (OECD) countries, to understand the driving forces behind sustained economic success. Since the simultaneous consideration of model uncertainty and parameter heterogeneity increases the number of candidate regressors beyond the processing capacity of ordinary BMA algorithms, the chapter introduces a modification of BMA called Iterative Bayesian Model Averaging (IBMA) to the growth literature.

The results of chapter 1 highlight different dimensions of parameter heterogeneity. First, while a large number of growth determinants are identified for the global sample, only a handful of these variables are also important for the Non-OECD sample. This result is surprising, given that the large number of Non-OECD countries were thought to provide most of the explanatory power of the global sample. Second, in Non-OECD countries a new set of regressors become highly effective. Third, and

[7] See Draper (1995) for a general discussion of model uncertainty, and Fernadez, Ley and Steel (2001) and Sala-i-Martin, Doppelhofer and Miller (2004) for pioneering applications of BMA in the growth context.

most devastatingly, the long list of variables included in the popular dataset employed, does not contain regressors that begin to satisfactorily explain the key growth determinants of high income countries. Thus, the chapter concludes that the results of the global sample have been debunked as artifacts of the combination of two heterogeneous subsamples, and policy recommendations should no longer be framed within the global framework.

A general similarity between high-income countries is their integration into global financial markets. To analyze whether financial integration constitutes a promising development strategy for developing countries, chapter 2 investigates the impact of financial openness on growth. While models based on competitive and efficient markets predict that financial openness should foster economic growth, the counter-argument stresses that in the presence of market distortions financial liberalization may lead to welfare reductions (see e.g. Bhagwati, 1998; and Stiglitz, 2000). This objection implies that the impact of financial openness on growth might be contingent on initial conditions, introducing threshold effects into the empirical link. Chapter 2 tests the robustness of the impact of financial openness on growth against a broad set of alternative growth determinants and allows for thresholds effects in the estimation strategy. It takes an agnostic view on thresholds and investigates a broad set of supportive initial conditions. The estimation approach allows to explicitly account for uncertainty about the nature of the threshold and therefore permits to assess the relative empirical support for different thresholds.

The results in chapter 2 provide substantial evidence of threshold effects in the link between financial openness and growth. In addition, the findings also reveal that the composition of flows matters for the growth outcome. The chapter finds that openness towards debt flows can lead to growth reductions in countries lacking basic supportive conditions. In contrast, FDI inflows generate growth benefits contingent on supportive country characteristics. A further important finding is that after explicitly taking into account threshold uncertainty, the number of effective thresholds is significantly reduced and institutional variables emerge as the only relevant class. In particular, the results suggest that corruption is the crucial threshold for beneficial FDI inflows, while a combination of both political and property rights institutions avert the risks of debt flows. These findings indicate that sound institutions constitute the crucial precondition for countries contemplating opening their capital account.

In contrast to the first two chapters, chapter 3 analyzes the growth experience of two particular countries over the period 1991-2004: Germany and the US. While the US experienced two successive labor productivity surges post 1995 and post 2000, Germany's productivity declined dramatically during the same period, signaling a departure from the technological frontier. To analyze the sources of the German productivity demise, a newly created database is used that allows for detailed industry-level comparisons with the US. Since a broad consensus has formed that the first productivity surge in the US is related to Information and Communication Technology (ICT), the essay pays special attention to the role of ICT in Germany.[8] The chapter employs the growth accounting framework pioneered by Jorgenson and Griliches (1967), which has been extensively employed in productivity analyses. The growth accounting methodology is especially suited since it allows tracing back aggregate productivity trends to detailed industries in a consistent framework. Further, it enables to analyze the three main channels through which ICT might impact growth: through increased ICT investment, technological progress in ICT producing industries, and spillovers from the use of ICT.

The results in chapter 3 reveal that ICT investment in Germany was deeply lacking behind the US in the mid nineties. While the transition to the new economy mitigated the German productivity slowdown, it could not reverse it. Slowing Non-ICT investment along with strong total factor productivity (TFP) declines in a few large industries were mainly responsible for the first productivity slowdown. After 2000, it is found that a recovery in Non-ICT investment was offset by a widespread collapse in German TFP growth. Over half of the German industries, accounting for almost 50% of German aggregate output, experienced negative TFP growth. This second major difference between the US and German industry performance explains Germany's secular departure from the technological frontier.

[8] See Jorgenson and Stiroh (2000), Oliner and Sichel (2000) for seminal contributions on the role of ICT for the US productivity surge in the mid nineties. Recently, Oliner, Sichel, Stiroh (2007) have confirmed these early conclusion taking into account several revisions of the official statistics.

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1 Unraveling the Fortunes of the Fortunate

An Iterative Bayesian Model Averaging (IBMA) Approach

1.1 Introduction

Over the last two decades there has been a massive effort to use cross-country datasets to identify key determinants of economic growth. Much of this empirical investigation has been based on the implicit assumption of homogeneity across countries, which led to a search for *global* determinants of growth. However, the assumption of homogeneity in cross-country growth regressions has been criticized repeatedly (see e.g. Temple, 2000; and Durlauf, Johnson and Temple, 2005). In general, this objection applies to any socioeconomic dataset but the assumption of a common underlying data generating process seems particularly inappropriate when analyzing such complex entities as countries (Brock and Durlauf, 2001).

The mounting evidence against "country homogeneity" has given rise to a literature investigating growth patterns in groups of countries that share common characteristics. This branch of research focuses either on particular variables (e.g., initial GDP) or particular regions (Africa, Latin America) that distinguish subsamples.[9] In this paper we revisit the issue of country heterogeneity but from a perspective that has been largely ignored by the empirical growth literature. We focus on identifying growth determinants in high-income (OECD) countries, to understand the structures that drive the riches in industrialized countries that developing nations attempt to emulate. In essence, our goal is to understand the driving forces behind sustained economic success, with the assumption that such successful growth paths are determined by a unique set of variables. Eicher and Leukert (2006) previously explored parameter heterogeneity among OECD and Non-OECD countries, but did not account for model uncertainty or a large number of potential regressors.

Our estimation approach includes both parameter heterogeneity, to allow countries to represent diverse objects, and model uncertainty, to account for the fact that economists do not know the single "true" growth model. More specifically, we utilize Bayesian Model Averaging (BMA) to address model uncertainty and expand the methodology to integrate structures that allow for the examination of parameter heterogeneity. Simultaneous consideration of model uncertainty and parameter hetero-

[9] See e.g. Easterly and Levine (1997), Brock and Durlauf (2001) and Masanjala and Papageorgiou (2007a, b).

geneity has previously been computationally prohibitive, as it exceeded the computational limits of existing model averaging algorithms. This is due to the large numbers of candidate regressors that emerge from the long list of potential growth regressors and relevant interaction terms that are required to test for parameter heterogeneity. To resolve the computation limitations we employ an innovative modification of BMA called Iterative Bayesian Model Averaging (IBMA) developed by Yeung, Baumgarner and Raftery (2005) for genomics applications. The key intuition of IBMA is that it applies traditional BMA iteratively on a reduced set of variables. Each iteration contains a set of variables that is sufficiently small to be processed by existing algorithms. Iterations continue until the complete set of candidate regressors has been processed at least once.

We obtain three key results that highlight different dimensions of country heterogeneity. First, of the large number of regressors that are effective in the global sample, only about half are also effective in the Non-OECD sample. This is surprising, since the large number of countries in the Non-OECD sample were thought to be providing most of the explanatory power for the global results. Secondly, our analysis shows that in Non-OECD countries new regressors become highly effective that were ineffective in the global sample. Many of these newly effective variables are highly intuitive, for example the primary export share, black market premium, average population age. Third, the OECD subsample shares few regressors with the global sample (6 out of 20); this leads us to conclude that the particular dataset does not contain the variables that identify determinants of growth of the fortunate in the past 30 years. There are also stark difference between OECD and the Non-OECD sample where only half of the variables overlap.

The rest of the chapter is organized as follows. Section 1.2 presents a summary of BMA and IBMA methodologies used in our econometric estimation. Section 1.3 discusses the cross-country dataset used, and presents the benchmark regression specification based on which we perform IBMA. This section also presents and examines the estimation results. Section 1.4 presents robustness analyses of our results to alternative modifications of the sampler used by IBMA. Section 1.5 concludes and offers directions for future research.

1.2 Estimation Methodology

The basic idea behind model averaging is to estimate the distribution of unknown parameters of interest across different models. The fundamental principle of model averaging is to treat models and related parameters as unobservable, and to estimate their distributions based on the observable data. In contrast to classical estimation, model averaging copes with model uncertainty by allowing for all possible models to be considered, which consequently reduces the biases of parameters.

Leamer (1978) first emphasized that the uncertainty inherent in competing theories should be accounted for in the empirical strategy. Levine and Renelt (1992) examine the robustness of cross-country growth determinants using Leamer's (1983) extreme bounds analysis. They show that the conclusions as to which regressors represent robust growth determinants depends on the researcher's test criteria. Extreme bound analysis has since been shown to be excessively strict, selecting too few "effective" regressors (see Sala-i-Martin, 1997, for a criticism of this approach relevant to growth regressions).

An additional drawback of extreme bound analysis has been the absence of a formal structure to manage the large number of possible models. Levine and Renelt (1992) choose to reduce the set of models to be examined by always including Initial Income, Investment Rates, Secondary School Enrollment Rate, and Population Growth Rate in each regression. Sala-i-Martin (1997) used the same method, but he chose to always retain Initial Income, Investment Rates and Life Expectancy. Fixing the number of regressors that must appear in each regression has a direct effect on the size of the estimated coefficients (see Leon-Gonzalez and Montolio, 2003) and it limits the number of models that are explored.

Since the first approaches to model uncertainty, a consensus has formed to apply Bayesian techniques to account for model uncertainty (see e.g. Fernandez, Ley and Steel 2001a, b; Brock and Durlauf, 2001; Sala-i-Martin, Doppelhofer and Miller 2004; and Masanjala and Papageorgiou, 2007a, b). Model averaging strategies asks the researcher to specify candidate regressors that are clearly linked to distinct and specific theories. Bayesian Model Averaging then allows for any subset of regressors to appear in a given model. This technique was first developed by Moulton (1991), and Palm and Zellner (1992), but computational issues initially hampered its implementation.[10] Since our methodology is based on BMA, we provide a brief overview of the method.

1.2.1 Bayesian Model Averaging

Bayesian Model Averaging (BMA) accounts for model uncertainty by averaging over all possible models, where each model's weight is given by its posterior model probability. The statistical foundation for BMA is documented extensively in excellent introductions by Raftery (1995) and Hoeting et al. (1999). Raftery (1995) and Raftery, Madigan and Hoeting (1997), followed by many others, have shown that BMA provides improved out-of-sample predictive performance compared to predictions that are conditioned on any one model.

We restrict ourselves to highlighting the crucial intuition behind the methodology and then provide an explanation of the specific approach that we implemented together with the methodological innovations. In typical cross-country growth regressions, model uncertainty arises due to the fact that the researchers must choose between regressors that are associated with competing theories. With k possible variables in a linear regression model, BMA potentially considers the entire model space of 2^k regression models. The posterior probability that BMA assigns is simply the conditional probability after all relevant data has been taken into account. Posterior probabilities are calculated using Bayes' theorem, utilizing the researcher-specified prior probability and the likelihood function.

Formally, consider n independent replications from a linear regression model where the dependent variable is per capita GDP growth, y, is regressed on an intercept, α, and candidate regressors chosen from a set of k variables in a design matrix Z of dimension $n \times k$. Assume that the rank of the matrix of regressors is $r(\iota_n : Z) = k + 1$, where ι_n is an n-dimensional vector of ones. Further define β as the full k-dimensional vector of regression coefficients. Now suppose we have an $n \times k_j$

[10] For further discussions on BMA and its potential uses see Draper (1995), Raftery, Madigan and Hoeting (1997) and Hoeting et al. (1999).

submatrix of variables in *Z* denoted by Z_j. Then denote by M_j the model with regressors grouped in Z_j, such that

$$y = \alpha\iota_n + Z_j\beta_j + \sigma\varepsilon, \tag{1}$$

where $\beta_j \in \Re^{k_j}$ $\left(0 \le k_j \le k\right)$ groups regression coefficients corresponding to the submatrix Z_j. The exclusion of any given regressor in a particular model implies that the corresponding element in β is zero. $\sigma \in \Re_+$ is a scale parameter and ε follows an *n*-dimensional normal distribution with zero mean and identity covariance matrix.

Since Bayesian Model Averaging allows for any subset of variables in *Z* to appear in any model M_j, thus there are 2^k possible sampling models. BMA specifies that the posterior inclusion probability of any given parameter of interest is the weighted posterior distribution of that quantity under each of the models. The specific weights are provided by each model's posterior model probability. The posterior inclusion probability can then be expressed as the weighted sum of the posterior probabilities of all models that contain the regressor of interest

$$P_{\Delta|y} = \sum_{j=1}^{2^k} P_{\Delta|y,M_j} P(M_j \mid y). \tag{2}$$

The posterior model probability itself is given by

$$P(M_j \mid y) = \frac{l_y(M_j)p_j}{\sum_{h=1}^{2^k} l_y(M_h)p_h}, \tag{3}$$

where $l_y(M_j)$, is the marginal likelihood of model M_j that is given by

$$l_y(M_j) = \int p(y \mid \alpha, \beta_j, \sigma, M_j)\, p(\alpha, \sigma)\, p(\beta_j \mid \alpha, \sigma, M_j)\, d\alpha\, d\beta_j\, d\sigma. \tag{4}$$

The sampled model corresponding to equation (1) is given by $p(y \mid \alpha, \beta_j, \sigma, M_j)$, and the priors for the intercept and the regressors are $p(\alpha, \sigma)$ and $p(\beta_j \mid \alpha, \sigma, M_j)$, respectively. We will define the priors below.

The implementation of Bayesian Model Averaging is subject to three challenges. First, the number of models that must be estimated increases with the number of regressors at the rate of 2^k. As a result, the number of summation entries in equations (2)-(3) can be enormous; a primary aim of BMA research has been to obtain efficient samplers that avoid exhaustive sampling. Such intensive calculations quickly become infeasible as 30 candidate variables imply over 1 billion candidate models. Second, the computation and evaluation of the integrals implicit in equation (4) may be difficult because they may not exist in closed form. In that case numerical solutions of the integral can further burden estimation efficiency. Third, the choice of the prior distribution specification is always contentious in Bayesian analysis. BMA requires the specification of two types of priors: a) prior model probabilities, $p(M_K)$, and b) prior parameter distribution $p(\theta_K, M_K)$.

With respect to the prior model probabilities we follow the common practice in the literature and assume a uniform distribution over the model space, which expresses each model as equally likely. It follows that the prior model probability is 2^{-k}, which renders the prior probability of including any given candidate regressor equal to 0.5 (see e.g., Raftery et al., 1997; and Fernandez, Ley and Steel, 2001a, b).[11]

The decision on the prior structure for the individual regressors is a potentially divisive issue. BMA requires the researcher to inject priors into the analysis, however these prior can be so diffuse that clear parallels to frequentist inference can be established. Extensive work has been conducted on the appropriate prior structure to obtain either data dependent priors (Raftery, Madigan and Hoeting, 1997), "automatic" priors (Fernandez, Ley and Steel, 2001b), or the Unit Information Prior (UIP). Eicher, Papageorgiou and Raftery (2007) systematically study the effects of model and regressor priors on predictive performance within a BMA framework to highlight the importance of a prior benchmark. Their software allows researchers to identify the appropriate prior structure for a given dataset.

[11] Mitchell and Beauchamp (1988) discuss the possibility of alternative model weights and Sala-i-Martin, Doppelhofer and Miller (2004) argue forcefully in favor of greater weights on smaller models. Brock, Durlauf and West (2003) suggest a tree structure to take into account similarities among regressors.

In our choice regarding the priors on the parameters space we follow Raftery (1995) and impose the diffuse UIP. The UIP can be derived from frequentist statistical principles (Kass and Wasserman 1995), and it is seen as a conservative prior that is sufficiently spread out over the relevant parameter values and reasonably flat over the area where the likelihood is substantial. Specifically, it is a multivariate normal prior with mean at the maximum likelihood estimate and variance equal to the expected information matrix for one observation (Raftery, 1999). It is also a special case of the preferred Fernandez, Ley and Steel (2001b) priors and it is closely related to the prior structure in Sala-i-Martin, Doppelhofer and Miller (2004). The advantage of the UIP is that it allows for a simple approximation of the marginal likelihood with the Bayesian Information Criterion (BIC). The BIC approximation is viewed as conservative fitness measure to evaluate model performance. If anything, BIC is biased against finding an effect of a given regressor (i.e. it favors the null hypothesis $\beta=0$).[12]

The one crucial departure from previous applications of model averaging in economics is our sampling and estimation methodology. Fernandez, Ley and Steel (2001a,b) use the Markov Chain Monte Carlo Model Composition (MC^3) sampling algorithm developed by Madigan and York (1995) to search the model space, while Sala-i-Martin, Doppelhofer and Miller (2004) use a "stratified" Coinflip sampler. MC^3 is a technique that allows for sampling of complex high dimensional distributions as it simulates a random walk across the search space to converge at a stationary posterior distribution. The MC^3 distribution of the sampled draws depends on the last value drawn. In contrast, the stratified Coinflip sampler samples one set of regressions using the prior probability sampling weights and then uses the approximate posterior inclusion probabilities calculated from those regressions for the subsequent sampling probabilities.

Given that MC^3's computational limit was no more than 60 candidate regressors,[13] the Coinflip sampler had the advantage of handling more candidate regres-

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[12] See e.g. Raftery (1995). For a more detailed discussion of the UIP and BIC, see Raftery (1999) and the discussion in Hoeting et al. (1999).

[13] At least until very recently. We have just discovered that the work of Ley and Steel (2007) extends the computational bound of MC^3 to 104 regressors. We discuss this development in the end of this section.

sors. However, the larger the search space the more difficult was for Coinflip sampler to converge. For example, in some BMA experiments we run with more than 70 candidate regressors there was no (or unacceptably slow) converge simply because the number of models becomes too large.

Our method follows Raftery (1995) who established that the UIP allows for a Laplace approximation of the marginal likelihood and thus renders a search across the entire model space obsolete. To further simplify the computational demands Raftery (1995) suggest the *Leaps And Bounds All Subsets Regression Algorithm* of Furnival and Wilson (1974) to reduce the candidate model space further.[14] The Leaps algorithm performs an exhaustive search for the best subsets of candidate variables for predicting the dependent variable in linear regression; it returns a specified number of best models for each model size.[15] Generally, the qualitative differences based on the different samplers are small but not negligible. Computationally, the Leaps sampler is by far the most efficient. This efficiency is crucial to handle the large number of models as we tackle model uncertainty and parameter heterogeneity by interacting the global variables with regional dummies, which substantially increases the size of candidate regressors.

1.2.2 Iterative Bayesian Model Averaging

The computational limit of the Raftery (1995) BMA algorithm (*bicreg*) is 54 candidate regressors. To address parameter heterogeneity, the interaction of regressors increases the domain of regressors from 41 to a possible 82, which implies 4 septillion (100 billion x 4 trillion) models. In addition, the simple act of interacting variables in a small dataset may lead the number of regressors to exceed the number of observation, such that the design matrix is no longer of full column rank.

To overcome these problems we introduce the Iterative BMA (IBMA) algorithm to economics that was initially proposed for a genome application by Yeung, Baumgarner and Raftery (2005). Specifically, they introduced IBMA to select a small number of relevant genes for accurate medical diagnoses from a pool of about 5000(!) genes. Our application is simpler. After interacting our 41 regressors with an

[14] See e.g. Raftery (1995) and Volinsky et al. (1997).

[15] Software to implement the Raftery method has been freely available since 1994 at Statlib (http://lib.stat.cmu.edu).

OECD treatment dummy and eliminating interaction terms that are perfectly collinear or have less than 2 observations, this leaves us with 77 candidate regressors (see the data discussion below).

The key intuition of IBMA is that it applies traditional BMA iteratively on a reduced set of variables, z, which is small enough to be processed by traditional BMA. We define z as the *regressor window*. For our application we choose a default size $z = 41$ and check for robustness below. After sorting the candidate regressors by their bivariate correlations with the dependent variable, they are added to the regressor window. After the first z regressors have been processed by the first BMA run, q variables whose posterior probabilities do not exceed a predetermined inclusion threshold (1 percent by default) are removed from the regressor window and q unprocessed candidate regressors are added. BMA is then applied again until all regressors have been considered.

There are some caveats that must be highlighted as the set of candidate regressors expands. One limiting factor for IBMA is related to the regressor window size. While models of size n are theoretically possible, IBMA cannot evaluate posteriors for models that exceed size z. Hence the procedure cannot lay claim to having examined the entire model space – which introduces possible inaccuracies if high quality models happen to be larger than z. In our robustness section we find that variations in z in IBMA do not alter our qualitative results in the growth dataset.

Although we provided this caveat, we can offer evidence that any concerns that z may not cover the relevant model size are unlikely to be applicable in cross-country growth regressions. Sala-i-Martin (1997) and Sala-i-Martin, Doppelhofer and Miller (2004) argue forcefully that the expected model size should not exceed 7 regressors. Prior work by Levine and Renelt (1992), Sala-i-Martin (1997), FLS and Sala-i-Martin, Doppelhofer and Miller (2004) never generated models with more than 18 potentially relevant regressors. Hence it is unlikely that high quality models in cross-country growth regressions contain more than 48 regressors.

New work by Ley and Steel (2007) extends MC^3 to potentially handle up to 104 regressors without the iterating procedure employed in our algorithm. The advantage being that the entire model space, including models up to 104 regressors can actually be considered. This also implies that the prior model size increases to perhaps an implausibly large number of regressor, however. It remains to be seen how accurate and time intensive the new MC^3 method generates convergence. Previous work using MCMC methods, particularly in applications with growth datasets, revealed that increasing the number of regressors (which of course increases the model space exponentially) resulted in considerable increase in computation time. Alternatively, IBMA is not limited to the number of candidate regressors and processes the data with stunning efficiency. It also allows the researcher to avoid having the prior model size increase linearly with the number of candidate regressors. Further research is necessary to examine how the three existing approaches to considering large model spaces (IBMA, modified MC^3 and BACE) compete in terms of efficiency and predictive performance. The unique advantage of IBMA over the other two approaches, at least to date, is that it is capable of considering applications like ours where the number of observations happens to be less than the number of potential regressors.

1.3 Estimation

1.3.1 The Data

For our analysis we adopt the FLS dataset. It is comprised of 41 variables and 72 countries of which 23 are OECD countries. In addition, we add a dummy variable to identify OECD countries. The dataset is a subset of the Sala-i-Martin (1997) dataset; it includes all variables that have previously been flagged as robustly related to growth and that do not entail a loss of observations. We choose the FLS dataset for several reasons. First, the dataset contains variables that proxy for a broad set of competing growth theories, such as human capital, institutional quality, religion, economic policy and geography. Hence, the dataset reflects the theory uncertainty inherent in growth econometrics that has been highlighted by Brock and Durlauf (2001). Second, the majority of the variables are measured at the beginning of the period or as close as possible to it, which reduces possible endogeneity problems that can potentially impact cross-country growth regression analyses. Finally, by choosing the same dataset as FLS we have a natural benchmark and reference point for our analysis.

Table 1.A1 in the appendix provides summary statistics for the global, OECD, and Non-OECD samples. The high income OECD countries grew on average almost twice as fast as the rest of the world over the period 1960-1992 (3 percent versus 1.7 percent). A first look at the data reveals some major initial advantages OECD countries possessed over the rest of the world. In 1960, initial GDP was about four times greater, life expectancy was 16 years greater and primary schooling was 28 percent higher in the OECD sample as compared to the Non-OECD sample. OECD economies also had effectively better institutions scoring higher on civil liberties, the rule of law and political rights[16], while ethnolinguistic fractionalization was twice as high in Non-OECD countries.

1.3.2 Model Specification

To examine the possibility of parameter heterogeneity, we examine whether the data generating process for the global sample is different from the data generating process of the OECD sample.[17] To model parameter heterogeneity we follow the approach suggested by Brock and Durlauf (2001) and Brock, Durlauf and West (2003) and treat parameter heterogeneity as a variable inclusion problem. It follows then that we can understand parameter heterogeneity as a special case of model uncertainty. We therefore modify the global equation in (1) and estimate the standard interaction model in empirical work of the following form:

$$y = \alpha \iota_n + Z_j \ \beta_{1,j} + I \ X_j \beta_{2,j} + \sigma\varepsilon, \tag{5}$$

where I is an indicator variable that equals 1 if the country is an OECD member and 0 otherwise. Z is the $n \times k$ matrix of the regressors and X is a sub-matrix of Z that excludes all variables that are either perfectly collinear in the OECD sample[18] or not relevant for the OECD sample due to negligible sub-sample variation.[19] In our case

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[16] Note that Civil Liberties and Political Rights are measured "backwards," i.e. larger values imply fewer civil liberties and political rights.

[17] Theoretical underpinnings for parameter heterogeneity are based on thresholds as in Azariadis and Drazen (1990), or on fully specified models of nonlinearities as in Galor and Weil (2000), Lucas (2002) and Galor and Moav (2002).

[18] The presence of multicollinearity exacerbates the problem of distinguishing between interaction terms that represent parameter heterogeneity and terms that are simply highly correlated with important interactions. This problem is neither unique to our issue at hand (OECD interaction), or IBMA.

[19] Excluded interactions are: Africa dummy, French Colony dummy, Fraction Hindu, Latin American dummy, Spanish Colony dummy, Fraction Confucian and Fraction Buddha.

with OECD interactions, the resulting model features 77 candidate regressors and 72 observations, which renders traditional BMA infeasible and leads us to implement the IBMA algorithm discussed above. The direct merit of the interaction model compared to subsample regressions is that the full information from the entire dataset is used to derive results.

Regression equation (5) can be interpreted as providing estimates for the control group, β_{1i}, which is in our case the sample of Non-OECD countries. It also provides the marginal effect experienced by the treatment group, β_{2i}, which are the OECD countries in our case. The actual impact of the *X* regressors for which we want to establish parameter heterogeneity can then be obtained by comparing the Non-OECD effect given by the posterior means of β_{1i} with the effect in OECD countries that is given by the composite means of $\widetilde{\beta}_i = \beta_{1i} + \beta_{2i}$.[20] Note that the definition of the composite $\widetilde{\beta}_i$ carries an important implication: If the Non-OECD effect, $\beta_{1,i}$, is observed to be significantly different from zero and the OECD effect is found to be insignificant, it implies either that the marginal estimate of the treatment group, β_{2i}, is estimated with great noise (e.g., with a high variance) to wash out any significance of the composite, or that the treatment effect is indeed quite tightly estimated, but of the opposite sign as, β_{1i}, rendering the composite $\widetilde{\beta}_i$ close to zero.

At this point it is important that the basic iterative routine suggested by Yeung et al. (2005) must be modified to assure that, β_{1i} and β_{2i} can appear in the same regression. Two cases are possible. In the first case, β_{1i} is included in a regressor window but the interaction is not (perhaps because its initial bivariate correlation was low). The rotation of each variable that is not in the initial regressor window does assure that β_{1i} and β_{2i} are in the final regressor window if they are both significant. In the second case, the initial regressor window includes β_{2i} but not β_{1i}, and the interaction alone is not significant. In this case the interaction will be rotated out of the regressor window and β_{2i} will never have the chance to actually interact with

[20] The composite variance is given by $\mathrm{var}(\widetilde{\beta}_i) = \mathrm{var}(\beta_{1i}) + \mathrm{var}(\beta_{2i}) + 2\mathrm{cov}(\beta_{1i}, \beta_{2i})$.

β_{1i}. This case requires a modification of the Yeung et al. (2005) procedure. In particular, we allow for two rotations in our version of IBMA. The first rotation (as suggested by Yeung et al. 2005) assures that all regressors that were not included in the initial regressor window will have a chance to be considered. The second rotation iterates all regressors that have been discarded from regressor windows in the first rotation (to make room for new regressors) once more through the window. This assures that even in the second case, an initially discarded interaction term will have the opportunity to eventually rejoin the global variable in a regressor window, if significant.[21]

Further considerations to assure that variables have been given due chance to exhibit their true interaction significance in IBMA led us to examine the final regressor window to see how many global terms were observed without interaction terms. As a robustness exercise, we executed final iterations that added interaction terms to match all significant global regressors whose interaction terms did not appear in the final regressor window. [22]

Our empirical strategy is to start by establishing the global BMA benchmark in Table 1.1. Here we initially examine the potential effectiveness of variables without any interactions specified in equation (5). Then we examine potential evidence for parameter heterogeneity. Finally we will examine robustness and compare different regressor window sizes in IBMA where we iterate until all covariates have been processed and the interaction terms are all included in the last iteration.

1.3.3 Results

Table 1.1 presents our baseline results applying IBMA to examine model uncertainty and parameter heterogeneity in the FLS dataset. In particular, Table 1.1 presents the coefficient posterior means, posterior standard deviation and the ratio of the absolute value of the former to the later, for the Global and Interaction specifica-

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[21] The Yeung et al. (2005) algorithm also suffers from the fact that it guarantees that the covariate with the lowest bivariate correlation is included in the final regressor window and hence in the final result. By adding regressors in the second rotation in inverse bivariate correlation order, we also improve on this design flaw.

[22] In additional robustness analysis, we also added one global regressor that was associated with one highly significant interaction term (Standard Deviation of the Black Market Premium) into the regressor window. This variable was found to be important for OECD but not robust across different windows considered. Our remaining results were unaffected.

tions. The value of the absolute value of the posterior mean to standard deviation ratio (post. mean/sd) is used as a measure for identifying variable effectiveness in our growth regression exercises. While the analysis of posterior inclusion probability speaks only to the probability of a candidate repressor's inclusion in the most effective models, we chose to emphasize the post. mean/sd ratio to better tie economic and statistical significance. Raftery (1995) suggested that for a variable to be considered as effective the posterior inclusion probability must exceed 50 percent; which is roughly equivalent of requiring a ratio of mean/sd = 1, which implies in frequentist statistics that the regressors improves the power of the regression. Hence, while Raftery's (1995) interpretation for BMA would imply a threshold value of the mean/sd ratio of about 1, we decided to be more stringent and set the threshold value equal to 1.3, which is roughly equivalent to a 90 percent confidence interval in frequentist hypothesis testing. We recognize that there is no consensus in the BMA literature about this threshold, but argue that our main results hold when this threshold is adjusted upwards or downwards.

The results for the interaction model are obtained by using IBMA with a regressor window of size z = 41. The choice of the regressor window size is natural in that it is directly comparable to the specification used to establish the benchmark results for the global sample. In Section 4 we report robustness results that vary z.

The dependent variable is growth 1960-1992 and the first column of Table 1.1 features all regressors that were found to be effective (post. mean/sd > 1.3) in the global, OECD, or the Non-OECD samples.[23] Columns 2 and 3 report the coefficients for the global sample. For this sample no interaction terms are employed, hence the number of regressors is only 41, which allows the use of standard BMA algorithms. Of the 41 regressors considered, Table 1.1 reports only the relevant 31 regressors with post. mean/sd > 1.3 to save space. All regressors excluded from the tables are ineffective in the global sample, in all subsample analyses, and in all robustness specifications.

[23] Posterior coefficient estimates in bold font represent those variables that pass the effectiveness threshold (post. mean/sd > 1.3).

Table 1.1: Effective Growth Determinants in Global and Interaction Models

	Global			Interaction		
	Posterior mean	Posterior s.d.	Posterior mean/s.d. ratio	Posterior mean	Posterior s.d.	Posterior mean/s.d. ratio
Intercept	**0.076**	0.017	4.385	**0.038**	0.017	2.234
OECD				**0.036**	0.018	2.014
GDP60	**-0.018**	0.002	8.122			
Non-OECD				**-0.013**	0.002	5.717
OECD				**-0.013**	0.002	5.483
LifeExp60	**0.001**	0.000	4.829			
Non-OECD				**0.001**	0.000	7.616
OECD				**0.001**	0.000	7.094
EQINV	**0.148**	0.036	4.145			
Non-OECD				**0.156**	0.033	4.786
OECD				**0.156**	0.033	4.752
Mining	**0.033**	0.012	2.823			
Non-OECD				**0.046**	0.010	4.44
OECD				**0.046**	0.011	4.357
OutOrient	**-0.003**	0.002	1.644			
Non-OECD				**-0.003**	0.002	1.358
OECD				**-0.003**	0.002	1.38
LatAmDum	**-0.013**	0.005	2.756			
Non-OECD				**-0.016**	0.003	4.539
HighEd60	**-0.121**	0.029	4.093			
Non-OECD				**-0.192**	0.044	4.375
OECD				-0.012	0.029	0.424
SubSahAfricaDum	**-0.022**	0.004	5.143			
Non-OECD				**-0.014**	0.003	4.073
EthnoFrac	**0.015**	0.004	3.775			
Non-OECD				**0.020**	0.005	3.64
OECD				0.006	0.006	0.897
HinduFrac	**-0.108**	0.020	5.349			
Non-OECD				-0.016	0.019	0.856
Lforce60	**0.000**	0.000	4.924			
Non-OECD				0.000	0.000	0.607
SpainDum	**0.014**	0.005	2.799			
Non-OECD				NA	NA	NA
FrenchDum	**0.011**	0.004	2.71			
Non-OECD				0.002	0.003	0.882
NonEqInv	**0.031**	0.021	1.474			
Non-OECD				0.012	0.016	0.753
OECD				0.011	0.017	0.665
ConfuciousFrac	**0.074**	0.010	7.225			
Non-OECD				NA	NA	NA
EngLangFrac	**-0.007**	0.004	1.507			
Non-OECD				0.000	0.001	0.144
PrimaryEd60	**0.020**	0.009	2.268			
Non-OECD				NA	NA	NA
Civlibb	**-0.002**	0.001	2.038			
Non-OECD				NA	NA	NA
BritDum	**0.007**	0.003	2.394			
Non-OECD				NA	NA	NA
RuleLaw	**0.013**	0.004	3.35			
Non-OECD				0.002	0.004	0.47
OECD				**-0.016**	0.011	1.453
BlackMktPrem	-0.004	0.004	1.216			
Non-OECD				**-0.012**	0.002	5.042
OECD				**-0.012**	0.002	5
EconOrg	0.000	0.001	0.567			
Non-OECD				**0.003**	0.001	4.235
OECD				**0.003**	0.001	3.927
PrimExp70	0.000	0.001	0.097			
Non-OECD				**-0.020**	0.004	5.014
OECD				**-0.017**	0.006	2.93
CathFrac	0.000	0.001	0.208			
Non-OECD				**0.013**	0.004	3.295
OECD				**0.013**	0.004	3.296
AvgPopAge	0.000	0.000	0.208			
Non-OECD				**0.000**	0.000	2.982
OECD				0.000	0.000	0.067
ProtFrac	-0.001	0.003	0.224			
Non-OECD				**-0.021**	0.010	2.083
OECD				0.004	0.005	0.723
BuddhaFrac	0.003	0.004	0.611			
Non-OECD				**0.018**	0.005	3.968
OthFracLang	0.000	0.001	0.108			
Non-OECD				**0.013**	0.003	3.99
OECD				-0.005	0.004	1.193

In the case of the global sample (columns 2, 3) no interaction terms are included, which implicitly assumes the absence of parameter heterogeneity. Here we replicate the results of the previous literature that assumes that OECD and Non-OECD countries are considered to have identical determinants of their growth performance, and that the magnitude of these determinants is also unchanged across subsamples. We find that in the global sample, 20 of the 41 candidate variables are effective to growth. The number and the type of regressors that we identify as effective is in line with the findings of the previous literature. For example, Equipment Investment, Dummies relating to the colonial history, Initial GDP, and specific country characteristics matter to growth as in Sala-i-Martin, Doppelhofer and Miller (2004); and FLS.

In columns 4 and 5 of Table 1.1 we report the results generated by allowing for the possibility of parameter heterogeneity related to the OECD group of countries. The subsample results are classified into seven subsets. First we have 5 variables that are effective in the global sample and in both the OECD and Non-OECD countries. These variables are Initial GDP, Initial Life Expectancy, Equity Investment, Mining and Outward orientation. This is the extent to which global, OECD and Non-OECD results agree. Second we find a set of 4 variables that are effective in both the global and Non-OECD samples, but are ineffective in the OECD sample. Variables in this set are Initial Higher Education, Ethnolinguistic Fragmentation, Sub-Saharan Africa, and the Latin Dummy. None of these variables have an impact in OECD countries. Two of these variables, the Sub-Saharan and Latin American Dummy, are simply irrelevant for OECD countries. For the other two the marginal contribution, β_2, in the interaction regression is highly significant and of the opposite sign as β_1, which renders the composite coefficient that indicates the OECD effect, $\widetilde{\beta}$, ineffective.

The third subset of results summarized in columns 4 and 5 of Table 1.1 is a relatively large set of 10 variables that are highly effective in the global sample, but once we allow for parameter heterogeneity neither the OECD nor the Non-OECD samples can claim these variables as growth determinants. Indeed in the interaction IBMA runs several of these variables do not pass the 1 percent posterior probability threshold and are not even included in the final regressor window that identifies the 41 top regressors. These cases are indicated with “NA.”

The fourth category consists of only one variable, Rule of Law, which is effective in the global and OECD samples but ineffective in the Non-OECD sample. The fifth category consists of 4 variables that are not effective in the global sample but highly effective in both the OECD and Non-OECD subsamples. The Fraction of Catholics and the Degree of Capitalism (EconOrg) both have a positive effect in the OECD and Non-OECD sample while the Black Market Premium and Primary Exports have a negative effect on growth in OECD and Non-OECD countries.

The sixth category consists of 4 variables that are ineffective in the global sample, but effective only in Non-OECD countries. This result confirms that adding high-income countries to the global mix may drown out important effects in the developing country’s subsample. The Average Population Age, the Fraction Protestant, Buddha and the Fraction of the Foreign Speaking Population are highly effective in Non-OECD countries but not in the global or OECD samples. Parameter heterogeneity thus uncovers not only crucial information as to what are not important growth determinants in advanced countries, but also new and important growth determinants in Non-OECD countries. Note that three of the variables that share importance in Non-OECD countries indicate a higher coefficient for the Non-OECD sample compared to the global sample. For two of these variables, Fraction Protestant and the Fraction of the Foreign Speaking Population, the impact in OECD countries is even opposite albeit ineffective. This is additional evidence that the inclusion of OECD countries in the sample drives down the growth impact of a variable for developing countries and may render it ineffective in the global sample. The seventh category consists of all variables that are ineffective in either the global, OECD or Non-OECD countries.

1.4 Robustness

The key innovation of IBMA is to apply the existing BMA structure iteratively to a computationally feasible subset of models, which we call the regressor window, z. In this section we examine the sensitivity of this novel aspect of IBMA analysis, as we vary the size of the regressor window. As indicated above, the previous growth literature established that between 4 and at most 18 variables matter in growth regressions, hence it would be surprising to obtain evidence from different window sizes that contradict our previous results. However, larger window sizes allow for more possible combinations of variables, some of which may not be able to attain the explanatory power unless they are placed in the models with a large number of regressors, yet others might not attain our threshold level of effectiveness unless they are jointly paired. The importance of such jointness has been emphasized by Doppelhofer and Weeks (2007) and Ley and Steel (2007). Table 1.2 reports the results for the global and the interacted sample from successively increasing the regressor window size. The practical computational limit is reached at a window size of $z = 48$.

To present the results most efficiently we have combined two columns in Table 1.1 to one individual column per window size that reports the global, OECD, and Non-OECD estimates for each relevant variable. Note that the Global estimate is only provided as a reference; it does not change throughout since the models for all 41 variables can be examined in BMA. Only the interaction that separates OECD and Non-OECD increases the number of regressors from 41 to 77, requiring the application of IBMA. Overall Table 1.2 documents robust results, but there are important changes that we discuss in detail.

Moving from $z = 41$ to $z = 45$ generates only a few differences in the results. For OECD countries we now find Mining to be ineffective while Non-Equipment Investment becomes effective. Additionally, we now find the Average Population Age, Fraction Protestant and the share of the Workforce to Total Population to be highly effective for OECD countries. For Non-OECD countries there are only two changes among the 41 growth determinants. The two additional variables that now register as marginally effective for Non-OECD Countries are Non-Equipment Investment and the Fraction Hindu, but otherwise there is no difference in the results. Most convincing perhaps is that the coefficient estimates are just about unchanged.

As we increased the size of the regressors window past $z = 45$, we find slightly augmented results. For the computationally most demanding run, $z = 48$, we find that a greater number of variables matter in both the global and the Non-OECD sample.

Table 1.2: Robustness Using Different Window Sizes in IBMA

	Regressor Window Size 41		Regressor Window Size 45		Regressor Window Size 47		Regressor Window Size 48	
	Post. mean	Post. s.d.	Post. mean	Post. s.d.	Post. mean	Post. s.d.	Post. mean	Post. s.d.
Intercept	**0.038**	0.017	**0.038**	0.017	**0.071**	0.014	**0.070**	0.015
OECD	**0.036**	0.018	**0.035**	0.021	**0.077**	0.026	**0.059**	0.027
GDP60	**-0.018**	0.002	**-0.018**	0.002	**-0.018**	0.002	**-0.018**	0.002
Non-OECD	**-0.013**	0.002	**-0.012**	0.002	**-0.015**	0.002	**-0.015**	0.002
OECD	**-0.013**	0.002	**-0.013**	0.002	**-0.015**	0.002	**-0.014**	0.002
LifeExp60	**0.001**	0.000	**0.001**	0.000	**0.001**	0.000	**0.001**	0.000
Non-OECD	**0.001**	0.000	**0.001**	0.000	**0.001**	0.000	**0.001**	0.000
OECD	**0.001**	0.000	**0.001**	0.000	**0.001**	0.000	**0.001**	0.000
EQINV	**0.148**	0.036	**0.148**	0.036	**0.148**	0.036	**0.148**	0.036
Non-OECD	**0.156**	0.033	**0.156**	0.033	**0.179**	0.032	**0.181**	0.034
OECD	**0.156**	0.033	**0.156**	0.033	0.052	0.046	**0.091**	0.063
Mining	**0.033**	0.012	**0.033**	0.012	**0.033**	0.012	**0.033**	0.012
Non-OECD	**0.046**	0.010	**0.041**	0.011	**0.029**	0.009	**0.027**	0.010
OECD	**0.046**	0.011	0.036	0.028	**0.032**	0.020	-0.016	0.067
OutOrient	**-0.003**	0.002	**-0.003**	0.002	**-0.003**	0.002	**-0.003**	0.002
Non-OECD	**-0.003**	0.002	**-0.003**	0.002	**-0.002**	0.001	**-0.003**	0.001
OECD	**-0.003**	0.002	**-0.003**	0.002	-0.002	0.002	**-0.003**	0.002
LatAmDum	**-0.013**	0.005	**-0.013**	0.005	**-0.013**	0.005	**-0.013**	0.005
Non-OECD	**-0.016**	0.003	**-0.016**	0.004	**-0.011**	0.003	**-0.013**	0.003
HighEd60	**-0.121**	0.029	**-0.121**	0.029	**-0.121**	0.029	**-0.121**	0.029
Non-OECD	**-0.192**	0.044	**-0.200**	0.047	**-0.111**	0.032	**-0.120**	0.029
OECD	-0.012	0.029	-0.025	0.033	**0.038**	0.028	**-0.119**	0.030
SubSahAfrica	**-0.022**	0.004	**-0.022**	0.004	**-0.022**	0.004	**-0.022**	0.004
Non-OECD	**-0.014**	0.003	**-0.016**	0.004	**-0.016**	0.002	**-0.017**	0.003
EthnoFrac	**0.015**	0.004	**0.015**	0.004	**0.015**	0.004	**0.015**	0.004
Non-OECD	**0.02**	0.005	**0.021**	0.005	**0.017**	0.004	**0.017**	0.004
OECD	0.006	0.006	-0.002	0.006	-0.003	0.005	0.000	0.006
HinduFrac	**-0.108**	0.020	**-0.108**	0.020	**-0.108**	0.020	**-0.108**	0.020
Non-OECD	-0.016	0.019	**-0.031**	0.020	**-0.083**	0.019	**-0.068**	0.013
Lforce60	**0.000**	0.000	**0.000**	0.000	**0.000**	0.000	**0.000**	0.000
Non-OECD	0.000	0.000	0.000	0.000	**0.000**	0.000	**0.000**	0.000
OECD	NA	NA	NA	NA	**0.000**	0.000	**0.000**	0.000
SpainDum	**0.014**	0.005	**0.014**	0.005	**0.014**	0.005	**0.014**	0.005
Non-OECD	NA	NA	NA	NA	**0.010**	0.003	**0.009**	0.003
FrenchDum	**0.011**	0.004	**0.011**	0.004	**0.011**	0.004	**0.011**	0.004
Non-OECD	0.002	0.003	0.002	0.002	**0.007**	0.003	**0.005**	0.002
NonEqInv	**0.031**	0.021	**0.031**	0.021	**0.031**	0.021	**0.031**	0.021
Non-OECD	0.012	0.016	**0.027**	0.017	**0.054**	0.014	**0.054**	0.014
OECD	0.011	0.017	**0.027**	0.017	-0.016	0.025	**-0.050**	0.029
EngLangFrac	**-0.007**	0.004	**-0.007**	0.004	**-0.007**	0.004	**-0.007**	0.004
Non-OECD	0.000	0.001	NA	NA	**-0.018**	0.006	-0.010	0.004
OECD	NA	NA	NA	NA	-0.001	0.004	NA	NA
Civlibb	**-0.002**	0.001	**-0.002**	0.001	**-0.002**	0.001	**-0.002**	0.001
Non-OECD	NA	NA	NA	NA	0.000	0.001	NA	NA
OECD	NA	NA	NA	NA	**0.008**	0.004	NA	NA
BritDum	**0.007**	0.003	**0.007**	0.003	**0.007**	0.003	**0.007**	0.003
Non-OECD	NA	NA	NA	NA	0.003	0.003	0.000	0.001
OECD	NA	NA	NA	NA	NA	NA	**0.017**	0.004
RuleLaw	**0.013**	0.004	**0.013**	0.004	**0.013**	0.004	**0.013**	0.004
Non-OECD	0.002	0.004	0.006	0.005	NA	NA	NA	NA
OECD	**-0.016**	0.011	**-0.037**	0.013	NA	NA	NA	NA
BlkMktPrem	-0.004	0.004	-0.004	0.004	-0.004	0.004	-0.004	0.004
Non-OECD	**-0.012**	0.002	**-0.011**	0.002	**-0.005**	0.002	**-0.006**	0.002
OECD	**-0.012**	0.002	**0.027**	0.008	0.005	0.011	**0.027**	0.007
EconOrg	0.000	0.001	0.000	0.001	0.000	0.001	0.000	0.001
Non-OECD	**0.003**	0.001	**0.003**	0.001	**0.002**	0.001	**0.002**	0.000
OECD	**0.003**	0.001	**0.003**	0.001	**0.002**	0.001	**0.002**	0.001
PrimExp70	0.000	0.001	0.000	0.001	0.000	0.001	0.000	0.001
Non-OECD	**-0.02**	0.004	**-0.021**	0.004	**-0.020**	0.003	**-0.021**	0.003
OECD	**-0.017**	0.006	**-0.021**	0.004	**-0.020**	0.003	**-0.021**	0.003
CathFrac	0.000	0.001	0.000	0.001	0.000	0.001	0.000	0.001
Non-OECD	**0.013**	0.004	**0.013**	0.004	NA	NA	NA	NA
OECD	**0.013**	0.004	**0.013**	0.004	NA	NA	NA	NA
AvgPopAge	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Non-OECD	**0.000**	0.000	**0.000**	0.000	**0.000**	0.000	**0.000**	0.000
OECD	0.000	0.000	**0.000**	0.000	0.000	0.000	**0.000**	0.000
ProtFrac	-0.001	0.003	-0.001	0.003	-0.001	0.003	-0.001	0.003
Non-OECD	**-0.021**	0.010	**-0.021**	0.008	-0.003	0.004	-0.001	0.004
OECD	0.004	0.005	**0.009**	0.005	-0.004	0.004	0.001	0.003
BuddhaFrac	0.003	0.004	0.003	0.004	0.003	0.004	0.003	0.004
Non-OECD	**0.018**	0.005	**0.018**	0.005	**0.019**	0.004	**0.015**	0.004
OthFracLang	0.000	0.001	0.000	0.001	0.000	0.001	0.000	0.001
Non-OECD	**0.013**	0.003	**0.012**	0.003	**0.010**	0.002	**0.010**	0.003
OECD	-0.005	0.004	0.000	0.004	-0.004	0.004	**-0.005**	0.003
PropRights	0.000	0.001	0.000	0.001	0.000	0.001	0.000	0.001
Non-OECD	NA	NA	NA	NA	**-0.002**	0.001	**-0.002**	0.001
OECD	NA	NA	NA	NA	-0.003	0.004	**-0.002**	0.001
WarDum	0.000	0.001	0.000	0.001	0.000	0.001	0.000	0.001
Non-OECD	NA	NA	NA	NA	**-0.004**	0.001	**-0.003**	0.002
OECD	NA	NA	NA	NA	-0.003	0.002	0.000	0.005
Worker/Pop	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Non-OECD	NA	NA	0.000	0.001	NA	NA	0.000	0.000
OECD	NA	NA	**-0.036**	0.009	NA	NA	**-0.037**	0.014

Note: Posterior coefficient estimates in bold font represent variables that pass our effectiveness threshold (post. mean/sd > 1.3).

Allowing for a larger window size increased the explanatory power for the Non-OECD determinants initial Labor Force, the Hindu Dummy, the Spanish Dummy, the French Dummy, and Non-Equipment Investment; every one of these variables was initially effective in the global sample, but ineffective in either sub-sample. In addition, the War Dummy and Property Rights are now also effective for Non-OECD, although they are not effective for the global sample. Two variables, the Fraction Catholic and Protestant now become ineffective. For OECD countries there are also a number of changes as 8 additional variables are added to the list of effective variables while 3 (Mining, Rule of Law and Fraction Catholic) are dropped from this list. On balance, however, the picture is unchanged as the evidence for parameter heterogeneity is overwhelming.

The clear break that signifies a large increase in the variables that are effective is at $z=45$. After z = 45 (see example for z = 47) the results are all closer to $z = 48$ than to z = 41, i.e. an effectively larger number of variables matters for growth in OECD and Non-OECD countries. However, we cannot identify a single variable that remains uniquely effective for OECD countries across the different window sizes. This is perhaps yet again more evidence that this dataset does not contain variables that are the unique growth determinants in this subset of countries.

The conclusions that can be reached from our robustness exercise are two-fold. First, most of our important benchmark results are quite robust to changes in the size of the regressor window. We caution though that these results have also revealed some fragility inherent in the regressor window approach inherent in the IBMA methodology. This should be kept in mind when one assigns particular interpretation to certain variables. Scrutinizing the causes for possible fragility of IBMA is beyond of the scope of this paper but we judge this as an important area for future research.

1.5 Discussion

In general our results suggest that the important determinants of long-term growth in Non-OECD countries overlap only to some degree with the factors identified with the global samples. For OECD countries this overlap is even smaller. In addition, allowing for parameter heterogeneity unveiled a large number of new variables that matter to only Non-OECD countries. However, allowing for parameter heterogeneity did not allow us to gain any meaningful insights into unique factors that determine growth in OECD countries.

We provide a Summary Table 1.3 to collect the results. Overall we find that a number of purported growth determinants in the global sample are not effective for Non-OECD countries, and that most established growth determinants do not show explanatory power for OECD countries. Even for Non-OECD countries, 11 of the original 20 effective variables are no longer effective. Instead, an entirely new set of variables matters in Non-OECD Countries, where 8 variables that were ineffective in the global sample are now shown to matter. While it is surprising to see some of the key variables in the global sample, such as Civil Liberties, Fraction Confucius, and Primary Education, loose their significance, the newly effective variables are all very much in line with established key indicators of growth in developing nations, such as the Degree of Capitalism, Primary Exports Share, and the Black Market Premium.

For the OECD the results are even more stunning. Of all the original 20 effective variables in the global sample only 6 survive as effective. The only variables added as effective for OECD countries by allowing for parameter heterogeneity are the Fraction of Population that is Catholic, Primary Exports, the Degree of Capitalism, and the Black Market Premium. The evidence for parameter heterogeneity is therefore overwhelming. Most variables in the global dataset do not matter for OECD countries, and half of the variables that matter for Non-OECD countries also do not matter for OECD countries. Note that this implies (as per our discussion in section 1.3.2) that the OECD treatment effect is highly significant *and of the opposite sign* as the Non-OECD effect to render the composite coefficient for the OECD, $\tilde{\beta}$, insignificant.

The combined analysis of parameter heterogeneity and model uncertainty has lead not only to quantitative differences regarding the effect of growth determinants across subsamples, but it also generated important new qualitative implications. To our surprise the quantitative (economic) differences between subsamples were minimal, because so few regressors are common across subsamples.

Table 1.3: Summary of Effective Growth Determinants

	BMA		IBMA with Interactions			
	$y = \alpha\iota_n + Z_j\beta_j + \sigma\varepsilon,$		$y = \alpha\iota_n + Z_j\beta_{1,j} + I\ X_j\beta_{2,j} + \sigma\varepsilon,$			
	Global Sample Effective Variables		Non-OECD Effective Variables		OECD Effective Variables	
	Posterior mean	Post. s.d.	Posterior mean	Post. s.d.	Posterior mean	Post. s.d.
BritDum	0.007	0.003				
Civlibb	-0.002	0.001				
ConfuciousFrac	0.074	0.010				
EngLangFrac	-0.007	0.004				
PrimaryEd60	0.02	0.009				
NonEqInv	0.031	0.021				
FrenchDum	0.011	0.004				
Lforce60	0.000	0.000				
HinduFrac	-0.108	0.020				
SpainDum	0.014	0.005				
LatAmDum	-0.013	0.005	-0.016	0.003		
FracEthno	0.015	0.004	0.020	0.005		
SubSahAfricaDum	-0.022	0.004	-0.014	0.003		
HighEd60	-0.121	0.029	-0.192	0.044		
EQInvest	0.148	0.036	0.156	0.033	0.156	0.033
LifeExp60	0.001	0.000	0.001	0.000	0.001	0.000
OutOrient	-0.003	0.002	-0.003	0.002	-0.003	0.002
Mining	0.033	0.012	0.046	0.010	0.046	0.011
GDP60	-0.018	0.002	-0.013	0.002	-0.013	0.002
RuleLaw	0.013	0.004			-0.016	0.011
CathDum			0.013	0.004	0.013	0.004
PrimExp70			-0.020	0.004	-0.017	0.006
BlackMktPrem			-0.012	0.002	-0.012	0.002
EconOrg			0.003	0.001	0.003	0.001
BuddhaDum			0.018	0.005		
AvgPopAge			0.000	0.000		
OthFracLang			0.013	0.003		
ProtFrac			-0.021	0.010		

Note: Column 4 reports composite means and the associated composite standards deviations. All variables that do not meet our effectiveness threshold (post. mean/sd <1.3) are not reported to save space.

Qualitatively we find not only that regressors may have opposite impacts in the different subsamples, indeed an entirely different set of regressors matters in the global, Non-OECD and OECD samples. While the relevant regressors for the global and Non-OECD sample can be recovered, the dataset does not contain the regressors necessary to explain the OECD growth performance.This is doubly tragic. First, policy recommendations to lower income countries can no longer be framed within the context that improvements in any of the variables in the dataset will actually lead to better growth outcomes. Hence we have no guidance as to what drives growth in high income countries. But even more disturbing, the growth performance in OECD countries was on average twice as high as in the Non-OECD samples, hence neither the determinants of the higher income levels, nor the higher income growth rates can be recovered given the current dataset. Two avenues can be explored to reconcile these findings. First we can collect data that has been linked specifically to growth in OECD countries (for example on regulation, see Nicoletti and Scarpetta et al. 2003). However, hopes of expanding such a dataset to the global sample are perhaps unrealistic. Second, the notion of one size fits all – or that one theory or one approach to growth can address the growth determinants in disparate subsamples – might be too optimistic.

1.6 Conclusion

This paper extends the literature on country heterogeneity in two dimensions. First, a new model averaging method called Iterative Bayesian Model Averaging (IBMA) is used to handle the exhaustive computation required when we simultaneously consider model uncertainty and parameter heterogeneity in our estimation. Second, instead of investigating the sources of growth (or lack of it) in low-income countries, we take a fresh look at what determines growth performance in the high-income OECD countries.

Our analysis suggests that IBMA is a powerful technique that makes it possible for researchers to consider a very large number of potential regressors. Our application of IBMA to growth empirics allows us to examine parameter heterogeneity and model uncertainty simultaneously in all regressor candidates. It reveals that a large number of regressors is highly effective for Non-OECD countries, but irrelevant for both, OECD countries and the global sample. Perhaps most surprising was our finding that the long list of growth determinants included in popular cross-country datasets does not contain variables that begin to identify the key determinants of growth in advanced countries. “Global” results that have been taken to represent some average coefficient estimate for all countries are now shown to provide little information about the growth determinants in two key subsamples. The Global results have been debunked as artefacts of the combination of two heterogeneous subsamples, and no longer as an expected impact that can identify effective growth determinants.

Appendix Chapter 1

Table 1.A1: Descriptive Statistics

	Global		OECD		Non-OECD	
Variable	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
Absolute Latitude	25.733	17.250	45.126	10.461	16.630	11.189
Age	23.708	37.307	39.043	41.877	16.510	33.006
Area (Scale Effect)	972.917	2051.976	1467.130	3036.055	740.939	1353.317
Black Market Premium	0.157	0.291	0.059	0.196	0.203	0.318
British Colony	0.319	0.470	0.174	0.388	0.388	0.492
Civil Liberties	3.466	1.712	1.758	1.148	4.268	1.295
Equipment Invest.	0.044	0.035	0.072	0.024	0.031	0.031
Ethnolinguistic Fractionalization	0.371	0.296	0.217	0.211	0.443	0.304
Fraction Catholic	0.422	0.397	0.427	0.392	0.420	0.403
Fraction of Buddhist	0.056	0.184	0.045	0.183	0.061	0.186
Fraction of Confucian	0.019	0.087	0.026	0.125	0.016	0.064
Fraction of Foreign Speaking Pop.	0.374	0.422	0.308	0.420	0.406	0.424
Fraction of Hindu	0.018	0.101	0.000	0.000	0.027	0.122
Fraction of Jews	0.013	0.097	0.002	0.005	0.018	0.117
Fraction of Mining to GDP	0.045	0.077	0.017	0.018	0.058	0.090
Fraction of Muslim	0.148	0.295	0.044	0.208	0.196	0.318
Fraction of Pop. speaking English	0.076	0.239	0.181	0.357	0.026	0.136
Fraction of Protestants	0.173	0.252	0.323	0.357	0.103	0.139
Fraction of years open	0.439	0.355	0.737	0.203	0.299	0.325
French Colony	0.125	0.333	0.000	0.000	0.184	0.391
GDP per capita 1960 (log)	7.492	0.885	8.399	0.622	7.066	0.633
Growth Rate of Population	0.020	0.010	0.009	0.007	0.026	0.006
Higher Education Enrolment, 1960	0.043	0.052	0.087	0.061	0.023	0.030
Latin American Dummy	0.278	0.451	0.043	0.209	0.388	0.492
Life Expectancy, 1960	56.581	11.448	67.948	5.986	51.245	9.298
Non-Equipment Invest.	0.149	0.055	0.183	0.037	0.134	0.055
Outward Orientation	0.389	0.491	0.435	0.507	0.367	0.487
Per Capita GDP Growth 1960-1992	0.021	0.018	0.030	0.011	0.017	0.019
Political Rights	3.451	1.896	1.589	0.993	4.324	1.558
Pop.60* Worker 60 (Scale Effect)	9305.375	24906.050	12814.540	16980.030	7658.217	27869.810
Primary Exports, 1970	0.673	0.299	0.379	0.230	0.811	0.217
Primary School Enrolment, 1960	0.795	0.246	0.971	0.066	0.713	0.256
Public Education Share	0.025	0.009	0.029	0.010	0.022	0.008
Ratio of Worker to Pop (log)	-0.954	0.189	-0.885	0.132	-0.986	0.204
Real Exchange Rate Distortion	121.708	41.001	105.783	16.605	129.184	46.709
Revolutions and Coups	0.182	0.238	0.071	0.122	0.235	0.261
Rule of Law	0.551	0.335	0.899	0.179	0.388	0.258
Spanish Colony	0.222	0.419	0.043	0.209	0.306	0.466
Standard Deviation of BMP	45.596	95.802	3.190	7.512	65.500	110.832
Sub-Saharan African Dummy	0.208	0.409	0.000	0.000	0.306	0.466
Type of Econ. Organization	3.542	1.266	4.217	0.736	3.224	1.343
War Dummy	0.403	0.494	0.130	0.344	0.531	0.504
Number of obs.	**72**		**23**		**49**	

Note: For Civil Liberties and Political Rights higher values imply lower civil liberties and political rights.

References Chapter 1

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2 Financial Openness and Thresholds Revisited

Accounting for Model Uncertainty

2.1 Introduction

Financial globalization is probably one of today's most controversially debated policy fields. While there are strong theoretical arguments in favor of free international capital flows – such as efficient global allocation of savings into their most productive uses, risk diversification leading to lower cost of capital (Henry, 2000) and/or production specialization (Obstfeld, 1994; Acemoglu and Zilibotti, 1997), and the potential of technology spillovers – the recent episodes of financial crises have cast doubt over these theoretical predictions. One important argument against growth benefits of financial integration stems from the theory of second best, which states that removing one distortion does not need to be welfare improving in the presence of other distortions (Lipsey and Lancaster, 1956). This objection, which has been emphasized in the context of financial globalization by Bhagwati (1998) and Stiglitz (2000), has important implications for developing countries that consider liberalizing their capital account. It postulates that financial openness may only be growth beneficial if certain supportive conditions are in place or *thresholds* overcome. Thus, the identification of relevant *thresholds* and the investigation of the relative importance of different *thresholds* are of crucial policy relevance.

While a growing body of literature investigates the relevance of particular thresholds, comprehensive analyzes of this topic are still scarce (Kose et al., 2006).[24] In this paper we offer an integrated framework to revisit the empirical relevance and robustness of threshold effects in the nexus between financial openness and growth. We take an agnostic view on the nature of the threshold and systematically examine all potential threshold theories that have been proposed in the literature in a common empirical framework. This comprehensive analysis further allows us to assess the relative importance of different thresholds. An important methodological innovation in our empirical strategy is the use of Bayesian Model Averaging (BMA) techniques to appropriately address the issue of *model uncertainty*.[25] In general, *model uncertainty* acknowledges that in economic theory competing theories or models exist to

[24] A notable exception is Edison et al. (2002).

[25] To our knowledge the only study accounting for model uncertainty in the financial openness literature is Durham (2004), who uses Leamer's (1983) extreme bound analysis. However, as discussed below extreme bound analysis has been criticized as not being soundly based on statistical and decision theoretic foundations.

explain the same phenomenon. In our context, *model uncertainty* arises due to uncertainty about the specification of the "true" growth model. In particular, the researcher investigating the link between financial openness and growth faces uncertainty about the control variables to include given the plethora of proposed growth determinants, about how the financial openness variable should enter the growth regression (linear vs. nonlinear), and about the specific threshold variable that might induce the nonlinearity.

Despite the large number of studies investigating the relationship between financial integration and growth, the empirical evidence remains inconclusive.[26] In the most comprehensive survey of this literature to date, Kose et al. (2006) state as one reason for the ambiguous evidence that studies differ in the set of included alternative growth determinants (see also Edison et al., 2004). This highlights the issue of model uncertainty and points to the fundamental problem of *theory open-endedness* in modern growth research (Brock and Durlauf, 2001). *Theory open-endedness* refers to the dilemma that the validity of a particular growth theory does not per se preclude the relevance of another theory. But even if researchers agree upon the relevant theories, there is still considerable uncertainty about which proxies to include in the growth regression.[27] Thus, given the limited number of observations, the researcher faces substantial uncertainty about the exact specification of the growth regression with respect to the control variables. By using model averaging, we are able to address the problems associated with the common practice of ad hoc specifications of the growth model and test the robustness of our claims against a broad set of alternative growth determinants.

A further important difference among studies, according to Kose et al. (2006), concerns the question of whether the effect of financial openness is homogeneous across countries. This question relates to the existence of threshold effects or more fundamentally parameter heterogeneity. A broad range of threshold variables have been proposed in the literature. These variables can be categorized into the following threshold theories: (i) *initial development* or income (e.g. Edwards, 2001); (ii) *insti-*

[26] For the most prominent examples in favour and against growth enhancing effects of financial openness see Quinn (1997) and Rodrik (1998), respectively.
[27] Durlauf, Johnson and Temple (2005) report, that more than 140 regressors have been identified as growth determinants corresponding to about 43 different growth theories.

tutional quality (e.g. Durham, 2004; Bekaert, Harvey and Lundblad, 2005); (iii) *domestic financial development* (e.g. Aoki, Benigno and Kiyotaki, 2006; Alfaro, Chanda, Kalemli-Ozcan and Sayek, 2004); (iv) *human capital* (Borensztein, De Gregorgio and Lee, 1998); (v) *macroeconomic stability* (e.g. Eichengreen, 2000; Arteta, Eichengreen and Wyplosz, 2003) or more specifically *trade openness* (e.g. Brecher and Diaz-Alejandro, 1977; Balasubramanyam, Salisu and Sapsford, 1996) and finally (vi) *ethno-linguistic heterogeneity* (Chanda, 2005). While studies allowing for the effect to vary across countries depending on initial conditions are in general more supportive of beneficial growth effects, considerable uncertainty about the existence of thresholds still remains (see e.g. Edison et al. 2002; Kraay, 1998). Our estimation approach enables us to address the uncertainty about thresholds or parameter heterogeneity. We do so by allowing the effect of financial openness to vary according to all threshold theories listed above.

As Kose et al. (2006) point out, a limitation of the existing studies on threshold effects is that they identify only the importance of one specific dimension without investigating the relative importance of different thresholds. This shortcoming is especially severe since the empirical relevance of one threshold has no bearing on the relevance of another. The importance, for instance, of an institutional threshold does not rule out the role of human capital as an important precondition. Without controlling for other potential thresholds, the finding of an important threshold might just be a manifestation of a misspecification due to omitted variables. We are able to appropriately address this issue by controlling for several thresholds simultaneously in our model averaging procedure. Thus we explicitly account for uncertainty about the "true" threshold model. By making probability statements about threshold parameters that account for the probability that each model in the space of potential models is the correct one, our procedure also allows to shed light on the question of the relative importance of different thresholds.

Our main results can be summarized as follows: First, in general we do not find a robust relationship between financial openness and growth in a simple linear specification. Second, once we allow the effect to vary depending on different country characteristics, however, our results provide strong evidence that financial openness indeed influences growth. Third, our results highlight the need to differentiate between different types of investment flows. We show that debt flows can actually retard growth while Foreign Direct Investment (FDI) inflows exert a robust positive impact in countries with favorable initial conditions. Fourth, after explicitly taking into account uncertainty with respect to different thresholds, we find exclusively institutional variables as effective thresholds. Most importantly, we uncover strongest evidence that the stock of FDI inflows is positively correlated with long term growth in countries characterized by sufficiently low levels of corruption.

The remainder of this chapter is organized as follows: the next section lays out the problem of model uncertainty in detail and presents the estimation approach to address the issue. Section 2.3 describes the data and Section 2.4 presents the results. The final section concludes.

2.2 Model Uncertainty and Estimation Approach

2.2.1 Model Specification and Uncertainty

Starting point of our estimation approach is the classical cross country growth regression due to Barro (1991), which is of the following form:

$$y = \alpha + S\beta + \varepsilon \tag{1}$$

y is a vector of country average per capita growth rates, S is a n x m matrix of growth determinants, and ε is vector of classical error terms, i.e. the errors are assumed to be normally distributed and have zero mean and constant variance σ. According to Brock and Durlauf (2001), the fundamental problem with growth regressions is to determine what variables are to be included in S. Given that growth theories are inherently *open-ended*, i.e. the validity of one theory does not imply the falsity of another, the researcher has to make a choice as to which growth theories to include. But even if there is agreement on the set of theories, there is still uncertainty about which proxies to include for a given growth theory. The problem is especially severe, since standard remedies such as estimating the full model is not feasible in the cross country growth context, given the limited number of countries and the large number of potential regressors (well over 140 according to Durlauf, Johnson and Temple, 2005). Therefore, the researcher has to make a choice about which variables to include and the incertitude associated with this selection process is known as *model uncertainty.*

Testing the growth impact of financial openness is further hampered by the uncertainty about the existence of threshold effects which introduce parameter heterogeneity into the regression equation (1). The theoretical literature is typically silent on how to exactly empirically specify parameter heterogeneity. A standard approach to allow for parameter heterogeneity is to introduce interaction effects between a financial openness measure and a measure that is assumed to be the relevant threshold variable. Following Brock and Durlauf (2001), and Brock, Durlauf and West (2003) heterogeneity uncertainty can then be treated as a variable inclusion problem. Thus, we can consider parameter heterogeneity as a special case of model uncertainty. In the following we are considering two different interaction models that we are going to estimate.

Our first approach to address threshold effects is to include a continuous interaction between our measure of financial openness and a third variable. Thus, we augment the standard cross country growth regression in the following way:

$$y = \alpha + S\beta + \beta_{FI1} fi + \beta_{FI2} fi * z + \varepsilon , \tag{2}$$

where fi is a measure of financial integration, S is again a n x m matrix of alternative growth determinants which act as control variables, and z is a possible threshold variable. In our case z is chosen out of the set of S for which this might be suggested by theory. The partial effect of financial integration on growth is then given by the estimate of the composite term $\beta_{FI1} + \beta_{FI2} z$.[28] Thus, the partial effect varies continuously over different levels of the threshold variable. The threshold value can then easily be calculated as $\bar{z} = -\frac{\beta_{FI1}}{\beta_{FI2}}$.

In addition, we estimate a second specification that also allows for heterogeneity of the financial openness parameter across countries. In this specification the effect of financial openness is assumed to vary across sub-groups of countries, however, the effect is constant *within* subgroups. Hence, this second specification pre-

[28] It follows then that the variance is given by $Var(\beta_{FI1}) + z^2 Var(\beta_{FI2}) + 2zCov(\beta_{FI1}, \beta_{FI2})$.

sumes that multiple regimes exist that are characterized by specific initial conditions. This approach is motivated by the theoretical growth literature that documents the existence of multiple steady states, and hence multiple growth regimes (e.g. Azariadis and Drazen, 1990). Empirical evidence was first provided by Durlauf and Johnson (1995). Our approach, however, is simpler in the sense that we only allow the effect of our regressors of interest, the financial openness measures, to vary across regimes. This assures comparability of the results to the first specification. Hence, we estimate the following regression model:

$$y = \alpha + S\beta + \beta_{FI1} fi + \beta_{FI2} fi * I + \varepsilon , \tag{3}$$

where I is an indicator function that equals 1 if $z > \bar{z}$ and z is again a variable out of the set of potential threshold theories. For example, if we consider initial income as the relevant threshold variable, this specification implies that the partial effect of financial openness on growth is given by β_{FI1} for low income countries and by the composite $\beta_{FI1} + \beta_{FI2}$ for the subgroup of high-income countries.[29] The coefficient estimate of the interaction between the financial openness measure and the regime dummy, β_{FI2}, represents the differential impact across regimes. One drawback of this approach is that theory provides no guidance as to what the appropriate threshold values $\bar{z}$ are. Thus, we exogenously divide the sample at two points: the 25% and the 75% quartiles. An advantage over the first approach is, however, that the construction of dummies mitigates the potential problem of measurement error in the continuous thresholds variables.

An additional source of uncertainty relates to the fact that there is no consensus as to which the relevant threshold variable z may be. As pointed out above a number of threshold variables have been proposed in the literature which can be broadly organized into the following theories: (i) initial development or income; (ii) institutional quality; (iii) domestic financial development; (iv) human capital; (v) macroeconomic stability and (vi) ethno-linguistic heterogeneity. And again, each theory is associated with a number of variables proxying for different aspects of that theory.

[29] The variance of the composite effect is given by $Var(\beta_{FI1}) + Var(\beta_{FI2}) + 2Cov(\beta_{FI}, \beta_{FI2})$.

As a consequence the number potential models increases even further and the issue of model uncertainty is aggravated.

Against the background of model uncertainty, the common approach in the financial openness literature to base interference on one or a few specifications seems difficult to justify. First the selection of the reported specifications can be criticized as arbitrary. Second and more importantly, the uncertainty in the selection process is not accounted for and thus underestimated (see Draper, 1995). As a consequence, neglecting model uncertainty potentially renders coefficient estimates "fragile" (e.g. Levine and Renelt, 1992; Brock and Durlauf, 2001). The fragility of coefficient estimates is important, since findings on the relationship between financial openness and growth that do not explicitly account for model uncertainty, may be non-robust.

Since the first approaches to model uncertainty pioneered by Leamer (1978), a consensus has formed to apply Bayesian Model Averaging (BMA) techniques to account for model uncertainty. BMA has been successfully applied in the context of linear cross country growth regressions (e.g. Fernandez, Ley and Steel, 2001a, b; Sala-i-Martin, Doppelhofer and Miller, 2004), as well as growth regressions that account for parameter heterogeneity (e.g. Masanjala and Papageorgiou, 2007; Eicher, Papageorgiou and Röhn, 2007) or threshold effects (Crespo Cuaresma and Doppelhofer, 2007). Note however, that despite the large number of growth determinants considered, none of the existing BMA studies has included a proxy for financial openness.

2.2.2 Bayesian Model Averaging

In this section we briefly explain the crucial intuition behind our BMA estimation methodology. For more extensive introductions the interested reader is referred to Raftery (1995), Raftery, Madigan and Hoeting (1997) or Hoeting et al. (1999).[30] An advantage of Bayesian Model Averaging over other approaches to deal with model uncertainty, such as extreme bounds analysis (Leamer, 1983, Levine and Renelt, 1992), is that BMA is soundly based on statistical theory with all results directly following from elementary probability theory, notably the definition of conditional probability, Bayes' theorem and the law of total probability. Intuitively: BMA

[30] For a more general introduction to Bayesian econometrics see e.g. Koop (2003).

asks the researcher to specify candidate regressors that are clearly linked to distinct theories. Bayesian Model Averaging then allows for any subset of regressors to appear in a given model. Given the data, BMA first estimates a posterior distribution of each regressor coefficient for every model that includes the regressor. It then combines all posterior distributions into a weighted average posterior distribution, with weights given by the posterior model probabilities.

For notational convenience we integrate the matrix S from above, the measure of financial openness and the interaction terms as either specified according to equation (2) or (3) into a comprehensive $n \times k$ matrix X. Then, consider a regression model, where the dependent variable per capita GDP growth, *y*, is regressed on an intercept, α, and candidate regressors chosen from a set of *k* variables in the design matrix *X* of dimension $n \times k$. Further define β as the full *k*-dimensional vector of regression coefficients. Now suppose we have an $n \times k_j$ submatrix of variables in X denoted by X_j. Then denote by M_j the model with regressors grouped in X_j, such that

$$y = \alpha + X_j \beta_j + \varepsilon, \tag{4}$$

where $\beta_j \in \Re^{k_j}$ $(0 \leq k_j \leq k)$ groups regression coefficients corresponding to the submatrix X_j. The exclusion of any given regressor in a particular model implies that the corresponding element in β is zero. Note that equation (4) incorporates parameter heterogeneity in our model averaging approach, since interactions with a measure of financial openness are part of the set of regressors *k*.

Since Bayesian Model Averaging allows for any subset of variables in *X* to appear in any model M_j, there are 2^k possible sampling models. BMA specifies that the posterior distribution of the slope coefficients β is the weighted posterior distribution under each of the models, $P(\beta \mid y, M_j)$, with the weights given by each model's posterior model probability $P(M_j \mid y)$. The posterior distribution given the data can then be expressed as

$$P(\beta \mid y) = \sum_{j=1}^{2^k} P(\beta \mid y, M_j) P(M_j \mid y). \tag{5}$$

Equation (5) is the fundamental equation of BMA. It states that the posterior distribution of the quantity of interest is only conditional on the data and *not* on a particular model. Inference based on the posterior distribution incorporates information across all possible models. The posterior model probability itself is given by

$$P(M_j \mid y) = \frac{l_y(M_j)}{\sum_{h=1}^{2^k} l_y(M_h)}, \tag{6}$$

where $l_y(M_j)$, is the marginal (or integrated) likelihood of model M_j.[31] Thus, the posterior model probability can be viewed as a measure of the relative data fit.

To investigate the role of thresholds in the link between financial openness and growth our estimation strategy proceeds in two steps. We begin by estimating equation (4) by only including one possible threshold variable at a time in the design matrix X. This approach assures comparability with previous approaches that have only investigated the importance of thresholds in one dimension. Nevertheless, this approach already allows us to examine the robustness of previous results by explicitly accounting for model uncertainty with respect to the inclusion of competing growth theories. Thus, in contrast to previous studies our results are not conditional on one particular model. A further advantage of only including one threshold variable at a time is that it allows for easy computation and interpretation of the composite effects. In a second step, we then extend the model space to include several thresholds. This approach explicitly addresses model uncertainty with regard to the threshold variables. It also allows us to directly assess the relative empirical importance of the different thresholds suggested in the literature.

[31] Note that equation (6) assumes a uniform prior over the model space, which is standard in the literature (see e.g. Fernadez, Ley and Steel 2001a, b). Computation of the marginal likelihood also requires the choice of parameter priors. Here we follow Raftery (1995) and Hoeting et al. (1999) and assume the diffuse Unit Information Prior (UIP) which allows for a simple approximation of the marginal likelihood with the Bayesian Information Criterion (BIC). In a recent paper Eicher, Papageorgiou and Raftery (2007) demonstrate that even though the choice of the appropriate prior structure crucially depends on the particular dataset considered, the UIP together with the *uniform model prior* is generally superior in terms of predictive performance to a range of alternative priors suggested in the growth context.

2.3 Data

2.3.1 Measures of Financial Openness

Our measures of financial openness are constructed from the recently updated and revised dataset of Lane and Milesi-Ferretti (2006), who create stocks of gross foreign liabilities and assets disaggregated into FDI, portfolio equity, debt, derivatives and official reserves. To measure the degree of financial integration, these stocks are expressed as ratios to GDP. Since different types of flows are usually associated with different growth effects (e.g. Reisen and Soto, 2001), an advantage of this dataset is therefore, that it allows to look at different types of flows in a common framework. We prefer these quantity based *de facto* measures of financial integration over widely used *de jure* measures based on the IMF's *Annual Report on Exchange Arrangements and Exchange Restrictions* (AREAER), since *de jure* measures do not capture the degree of enforcement of capital controls and, thus, do not always reflect the actual degree of integration of economies into global capital markets (see Kose et al., 2006). Further, Aizenman and Noy (2006) report that de jure restrictions on the capital account have no impact on de facto financial integration, and Magud and Reinhard (2006) conclude that controls on inflows do not reduce the volume of net flows.[32] The advantage of the stock measure over flow data is that stock data are less volatile and by construction as accumulated flows incorporate historic information about the financial integration of a country. Moreover, as Kose et al. (2006) point out, by accounting for valuation effects stock measures are also more appropriate to measure risk sharing motives.

One drawback of de facto measures is that they are likely to be endogenous in growth regressions. We believe that stock measures are less affected than flow measures. However, to further mitigate the possible endogeneity problem we focus exclusively on beginning of the period values. As pointed out above, by construction as accumulated flows the stock measures incorporate a historic dimension, which additionally alleviates the endogeneity problem.

[32] For an extensive survey of the different measures of capital account restrictions see also Edison et al. (2004).

2.3.2 Other Data

We employ a cross sectional dataset for 72 countries with average real per capita GDP growth over the period 1980-2000 as the dependent variable. With regard to other growth determinants, as discussed above, our aim is to test the robustness of financial openness against the broad spectrum of competing growth theories. Thus, to account for theory uncertainty, we nest the theory of financial openness within a larger model space that accounts for recent fundamental as well as more proximate growth theories. A well known problem in growth regression is the endogeneity of regressors. We try to limit endogeneity by measuring the great majority of explanatory variables before or at the beginning of the period under investigation. In the following we briefly describe the included growth theories. A detailed description of the variables as well as the sources can be found in Table 2.A1 in the appendix.

To reflect the ongoing debate over the primacy of *institutions* (e.g. Hall and Jones, 1999; Acemoglu et al., 2001, 2002, 2005; Rodrik, Subramanian, and Trebbi, 2002) versus *geography* (e.g. Sachs, 2003) as the fundamental causes of growth, we include political and economic institutions on the one hand and variables that proxy for a country's climate and initial endowments on the other hand. The importance of ethno-linguistic *fractionalization* has been shown for example by Easterly and Levine (1997) and more recently by Alesina et al. (2003) and thus we add regressors that portray a county's level of fractionalization. Additionally, to represent more proximate growth theories, we incorporate the variables from the canonical *Solow* framework; *human capital* measures, which figured prominently in the augmented Solow Model (e.g. Mankiw, Romer and Weil, 1992) and endogenous growth theories (e.g. Lucas, 1988); and a proxy for *domestic financial development* (Levine, 2005). Even though some authors argue that *macroeconomic policies* are simply symptoms of deeper institutional causes (e.g. Acemoglu et al., 2003), we follow the standard practice in the empirical growth literature and include a so-called policy conditioning set. Finally, as a separate theory we also consider *regional heterogeneity*.[33]

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[33] In this set we also include the fraction confucious, which has been found as one of the most robust growth determinants in the BMA exercises of Fernandez, Ley and Steel (2001a) and Sala-i-Martin, Doppelhofer and Miller (2004).

2.4 Results

2.4.1 Benchmark Linear Specification

As a benchmark, we first consider possible linear effects of financial openness on growth, i.e. we do not allow for any threshold effects. Table 2.1 displays the results. In the first panel of Table 2.1 we employ the broadest measures of financial openness, Total, which covers the stock of all external assets and liabilities as a fraction of GDP. In the second and third panel of Table 2.1 we disaggregate Total into its most important components: the stock of equity assets and liabilities, Equity Total, and the stock of debt assets and liabilities, Debt Total. Finally, in the fourth and fifth panel we focus on accumulated equity inflows (liabilities) disaggregated into FDI liabilities and portfolio equity liabilities. These equity inflows are usually associated with the greatest growth benefits (e.g. Soto and Reisen, 2001). The first and second column of each panel shows the posterior mean and standard deviation, respectively. The third column displays the ratio of the posterior mean to the posterior standard deviation in absolute terms. This ratio is used as a measure to identify effective growth determinants. While posterior inclusion probabilities capture the probability of a regressor's inclusion in the most effective models, we focus here on the posterior mean and standard deviation (mean/sd) ratio to better tie economic and statistic significance.[34] Following Eicher, Papageorgiou and Röhn (2007) we set the threshold value equal to 1.3, which is roughly equivalent to a 90% confidence interval in frequentist hypothesis testing.[35] We recognize that there is no consensus in the BMA literature about this cut-off point, however, our results are robust to reasonable adjustments.

Turning to the results of Table 2.1, we in general do not find any evidence of a robust linear relationship between financial openness and growth, with 4 out of the 5 measures having a posterior mean/sd ratio close to zero. The only exception is FDI

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[34] A decision theoretic foundation for this ratio is given by Brock and Durlauf (2001).

[35] Raftery (1995) suggested that for a variable to be considered as effective the posterior inclusion probability must exceed 50 percent; which is roughly equivalent of requiring a ratio of mean/sd = 1, which implies in frequentist statistics that the regressors improves the power of the regression. Along with Eicher, Papageorgiou and Röhn (2007) we decided to be more stringent and set the threshold value equal to 1.3.

Table 2.1: Linear Effects of Financial Openness on Growth

	(1)			(2)			(3)			(4)			(5)		
Variable	**Post mean**	**Post s.d.**	**Post mean/ sd ratio**	**Post mean**	**Post s.d.**	**Post mean/ sd ratio**	**Post mean**	**Post s.d.**	**Post mean/ sd ratio**	**Post mean**	**Post s.d.**	**Post mean/ sd ratio**	**Post mean**	**Post s.d.**	**Post mean/ sd ratio**
Intercept	-3.46	4.79	0.72	-3.46	4.79	0.72	-3.46	4.79	0.72	1.49	6.14	0.24	-3.45	4.78	0.72
lngdp	**-1.86**	**0.51**	**3.67**	**-1.86**	**0.51**	**3.66**	**-1.86**	**0.51**	**3.67**	**-1.69**	**0.49**	**3.44**	**-1.86**	**0.51**	**3.67**
lnpopgr	**-4.19**	**1.95**	**2.15**	**-4.19**	**1.95**	**2.15**	**-4.19**	**1.95**	**2.15**	**-3.45**	**2.08**	**1.66**	**-4.19**	**1.94**	**2.15**
life	**0.16**	**0.05**	**3.16**	**0.16**	**0.05**	**3.15**	**0.16**	**0.05**	**3.16**	**0.10**	**0.07**	**1.38**	**0.16**	**0.05**	**3.16**
confuc	**6.88**	**3.15**	**2.19**	**6.88**	**3.15**	**2.18**	**6.88**	**3.15**	**2.19**	**6.67**	**2.97**	**2.25**	**6.88**	**3.15**	**2.19**
mining	**5.64**	**2.78**	**2.03**	**5.64**	**2.78**	**2.03**	**5.64**	**2.78**	**2.03**	1.63	2.98	0.55	**5.65**	**2.77**	**2.04**
sub	**-1.45**	**0.90**	**1.61**	**-1.45**	**0.90**	**1.61**	**-1.45**	**0.90**	**1.61**	**-1.65**	**0.83**	**1.98**	**-1.45**	**0.90**	**1.61**
primenrol	**-0.02**	**0.01**	**1.33**	**-0.02**	**0.01**	**1.33**	**-0.02**	**0.01**	**1.33**	0.00	0.01	0.47	**-0.02**	**0.01**	**1.32**
east	0.71	0.89	0.79	0.71	0.89	0.79	0.71	0.89	0.79	**1.59**	**1.00**	**1.59**	0.71	0.89	0.79
kgatrstr	-0.21	0.55	0.39	-0.21	0.55	0.39	-0.21	0.55	0.39	**-1.27**	**0.92**	**1.37**	-0.22	0.55	0.39
corr	0.22	0.22	1.00	0.22	0.22	1.00	0.22	0.22	1.00	0.19	0.21	0.91	0.22	0.22	1.00
language	0.65	0.89	0.73	0.65	0.89	0.73	0.65	0.89	0.73	0.57	0.83	0.69	0.66	0.90	0.73
bureau	0.10	0.20	0.51	0.10	0.20	0.51	0.10	0.20	0.51	0.06	0.16	0.39	0.10	0.20	0.50
openk	0.00	0.00	0.47	0.00	0.00	0.47	0.00	0.00	0.47	0.00	0.00	0.18	0.00	0.00	0.47
pr	-0.04	0.10	0.40	-0.04	0.10	0.40	-0.04	0.10	0.40	-0.22	0.17	1.29	-0.04	0.10	0.40
laam	-0.11	0.37	0.31	-0.11	0.37	0.31	-0.11	0.37	0.31	-0.06	0.28	0.20	-0.11	0.37	0.31
lnki	-0.13	0.43	0.30	-0.13	0.43	0.30	-0.13	0.43	0.30	-0.30	0.60	0.50	-0.13	0.44	0.31
ethnic	-0.15	0.55	0.28	-0.15	0.56	0.28	-0.15	0.55	0.28	-0.08	0.42	0.19	-0.15	0.55	0.28
ecorg	0.01	0.06	0.21	0.01	0.06	0.21	0.01	0.06	0.21	0.00	0.01	0.03	0.01	0.05	0.20
invprof	0.01	0.05	0.21	0.01	0.05	0.21	0.01	0.05	0.21	0.04	0.10	0.43	0.01	0.05	0.21
secenrol	0.00	0.01	0.21	0.00	0.01	0.21	0.00	0.01	0.21	0.00	0.01	0.42	0.00	0.01	0.21
tertenrol	0.00	0.00	0.11	0.00	0.00	0.11	0.00	0.00	0.11	-0.01	0.02	0.36	0.00	0.00	0.11
govcons	0.00	0.00	0.05	0.00	0.00	0.05	0.00	0.00	0.05	0.00	0.01	0.10	0.00	0.00	0.05
cl	0.00	0.02	0.05	0.00	0.02	0.05	0.00	0.02	0.05	0.00	0.00	0.01	0.00	0.02	0.05
inflation	0.00	0.00	0.05	0.00	0.00	0.05	0.00	0.00	0.05	0.00	0.00	0.11	0.00	0.00	0.06
oecd	0.00	0.03	0.03	0.00	0.03	0.03	0.00	0.03	0.03	-0.04	0.22	0.17	0.00	0.03	0.02
lcr100km	0.00	0.03	0.02	0.00	0.03	0.02	0.00	0.03	0.02	-0.03	0.21	0.15	0.00	0.02	0.02
law	0.00	0.01	0.02	0.00	0.01	0.02	0.00	0.01	0.02	0.00	0.00	0.00	0.00	0.01	0.02
priexp	0.00	0.02	0.01	0.00	0.02	0.01	0.00	0.02	0.01	0.00	0.05	0.03	0.00	0.00	0.00
privo	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
religion	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.01
lnbmp	0.00	0.01	0.01	0.00	0.01	0.01	0.00	0.01	0.01	0.00	0.00	0.00	0.00	0.01	0.01
yrsopen	0.00	0.01	0.00	0.00	0.01	0.00	0.00	0.01	0.00	0.00	0.03	0.02	0.00	0.01	0.00
total	0.00	0.00	0.00												
equitytotal				0.00	0.05	0.02									
debttotal							0.00	0.00	0.00						
fdiliab										**2.88**	**2.09**	**1.38**			
portliab													-0.08	1.35	0.06
No of obs.		72			72			72			72			72	

Notes: Entries in **boldface** represent those variables that pass the effectiveness threshold (post. mean/sd >1.3)

liabilities for which we find weakly positive evidence, with a posterior mean/sd ratio of 1.38 slightly exceeding our effectiveness threshold. These results, however, are not surprising given the difficulties of the previous literature to establish unconditional effect even without explicitly accounting for model uncertainty with respect to alternative growth determinants. Yet, the findings could arise due to a misspecification of the empirical model. In fact, as described in detail above, it is reasonable to assume that the effects of financial openness are contingent on supportive initial conditions, which introduce thresholds or more generally parameter heterogeneity into the financial integration growth nexus. This is what we are going to investigate in more detail in the next sections.

With respect to the other regressors, our results are broadly in line with the existing literature on robust growth determinants (see e.g. Fernandez, Ley and Steel, 2001a; and Sala-i-Martin, Doppelhofer Miller, 2004). More specifically, we find that the Solow variables initial GDP and the population growth rate, as well as life expectancy, the fraction confucious and the sub Saharan Africa dummy are effective growth determinants across all specifications with the expected signs. In the case of FDI this list is slightly augmented. Additionally, the East Asia dummy and a variable relating to geography - the fraction of land in tropical and subtropical area – emerge as effective growth determinant. Both of these variables were also flagged as robust growth regressors in Sala-i-Martin, Doppelhofer and Miller (2004).

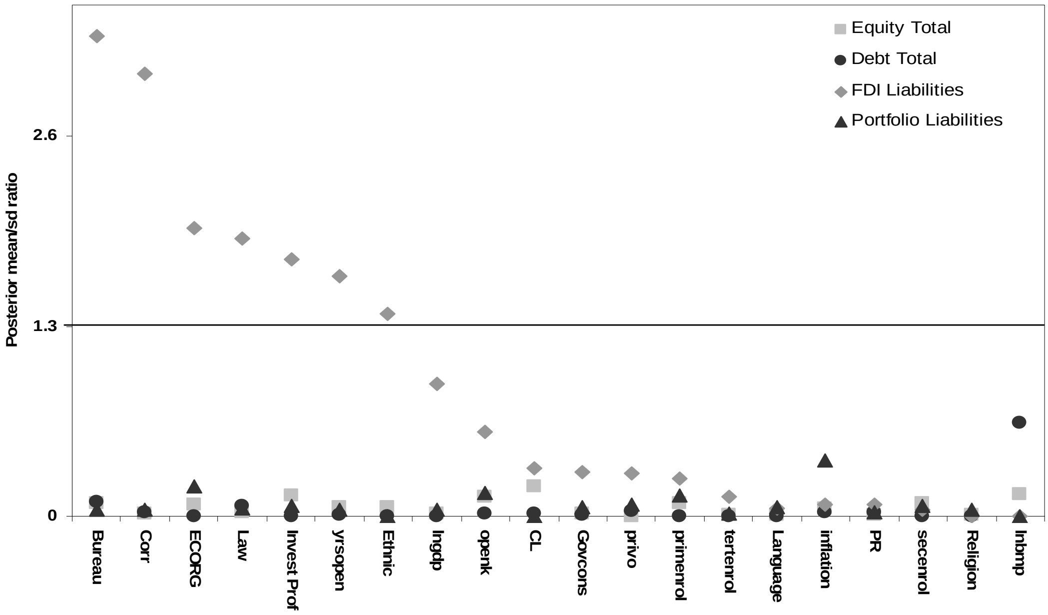
2.4.2 Continuous Interaction Approach

As a first approach to account for possible threshold effects we estimate equation (2) using our BMA methodology. As described above this approach allows the partial effect of financial openness to vary continuously with the level of some threshold variable. To give a first overview of the results, Figure 2.1 plots the posterior mean/standard deviation ratios of the interaction terms for each of the potential threshold variables with our financial openness measures.[36] A posterior mean/standard deviation ratio of an interaction term above 1.3 indicates evidence of parameter heterogeneity. An important observation from Figure 2.1 is that we only find support for parameter heterogeneity for the case of FDI liabilities. For all other measures none of the interaction term's posterior mean/sd ratio exceeds 1.3. While these results are important in their own right, since they suggest that for the case of FDI the linear model is misspecified, they do not yet inform us about potential thresholds. To investigate thresholds, we need to focus on the composite effects. This is what we turn to next.

Figure 2.2 plots the composite mean estimates – the partial effect of FDI on growth - along with 1.3 standard deviation bands as a function of each of the 7

[36] Henceforth we will not report results for Total anymore, but focus on the more disaggregated measures instead.

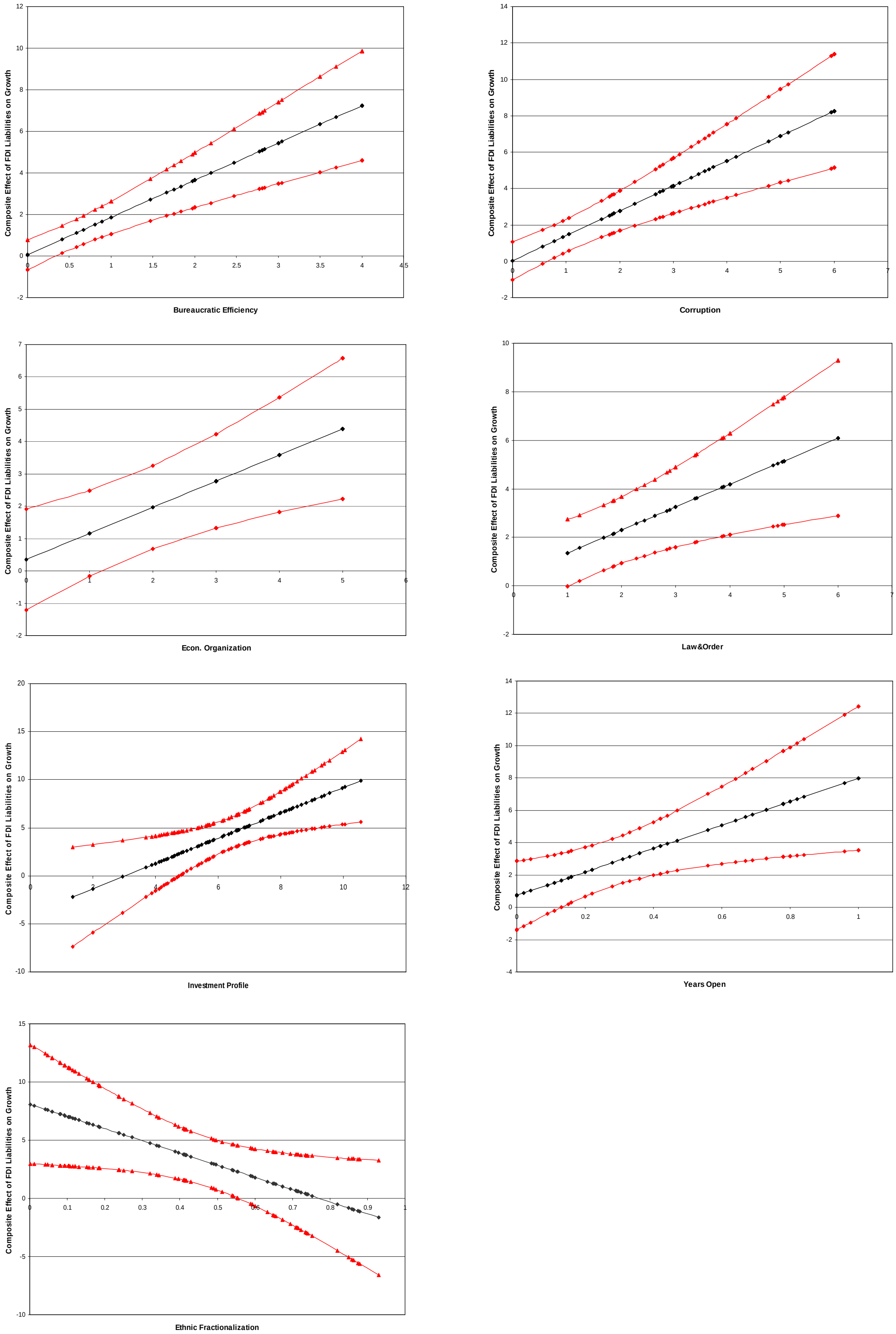
Figure 2.1: Posterior Mean/Standard Deviation Ratio of Interaction Terms – Continuous Interaction Approach



variables, for which we found evidence for parameter heterogeneity above. Table 2.A2 in the appendix presents the detailed results for these BMA runs. Inspection of the composite means reveals some interesting observations. When FDI is interacted with bureaucratic efficiency, corruption, economic organization and law&order, we find that the composite effect is positive over the entire range of observations. Further, in all of these cases the composite means are 1.3 standard deviations above zero, i.e. the composites pass our effectiveness threshold, for at least 90% of the observations in our sample. Thus, these findings suggest, that while these four variables exhibit an important quantitative impact on the marginal effect of FDI on growth, they do not suggest a qualitatively differential impact across countries.

The composite effect is also positive over the entire range of observations of the variable years open. However, FDI is only effective for about 70% of the countries in our sample characterized by high values in the trade openness measure. Moreover, when we focus on the composite effect of FDI as functions of investment profile or ethnic fractionalization, we observe that the composite effect can in fact turn negative. In particular, the composite effect turns negative for values in the investment profile indicator of below 3 (corresponding to the level of Chile), and for

Figure 2.2: Estimated Composite Effects of FDI Liabilities over the Observed Range of Threshold Variables



Notes: The black line represents the composite coefficient estimate, and the grey lines the 1.3 standard deviation bands.

values above 0.77 (corresponding to the level of South Africa) in the index of ethnic heterogeneity. Further, our estimates of the standard deviation imply that FDI constitutes an effective growth determinant for only 64% of the countries in our sample that feature low levels of ethnic heterogeneity (values below 0.56). The same is true for 75% of the countries in our sample characterized by high values in the investment profile indicator (values above 4.75). Hence, in addition to introducing parameter heterogeneity, we also find that these variables have significant qualitative implications, acting as thresholds in the link between FDI and growth.

In this section we have investigated one specific form of nonlinearity between financial openness and growth. The results in this section already revealed some evidence for thresholds for the case of FDI. In the next section we will investigate an alternative empirical specification of nonlinearities and will find that the evidence of thresholds is reinforced and even more striking.

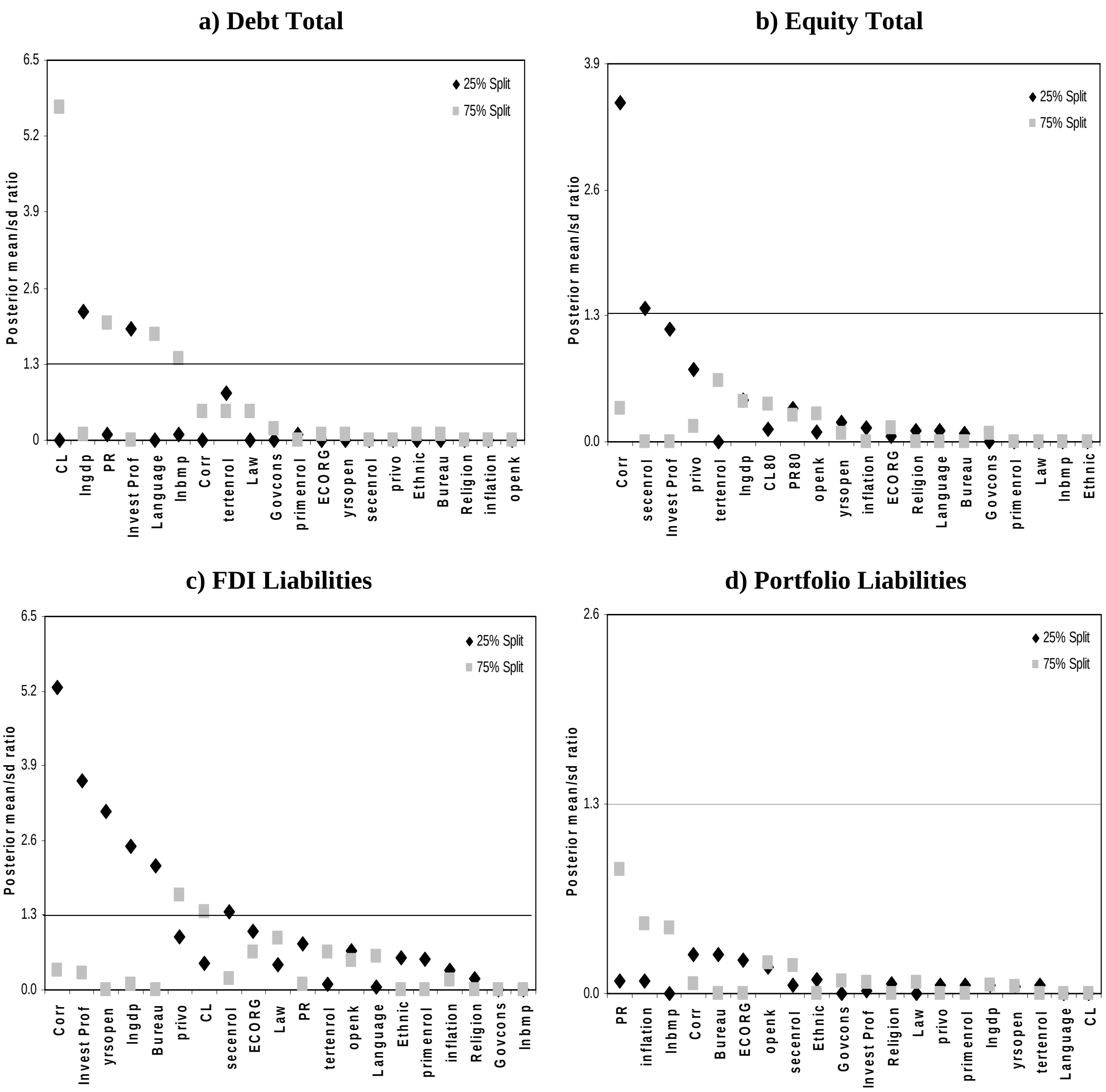
2.4.3 Regime Approach

In this section, we turn to the results of our second estimation approach. Thus, we estimate equation (3) using BMA. As described in the methodology section, for each of the possible threshold variables we introduce two dummy variables that equal one if the observation is above the 25% quartile or the 75% quartile, respectively.[37] Figures 2.3a-d provide an overview of the results. The figures display the posterior mean/sd ratios of the interactions between the regime dummy and our measures of financial openness. A posterior mean/sd ratio above 1.3 indicates evidence that the effect of financial openness varies effectively across regimes.

Compared to our first approach, the Figures 2.3a-d indicate even stronger evidence of parameter heterogeneity. Most importantly, in contrast to the results of the continuous interaction approach, we now also find support for parameter heterogeneity for Debt Total and Equity Total. The results for FDI are augmented compared to the continuous interaction case. In particular, similar to the continuous case we find effective interactions with corruption, investment profile, bureaucratic efficiency and years open. However, we additionally discover parameter heterogeneity with respect

[37] We also experimented with splitting the sample at the median, and the results were qualitatively very similar. However, we found a smaller number of effective thresholds.

Figure 2.3: Posterior Mean/Standard Deviation Ratio of Interaction Terms – Regime Approach



to initial income, financial intermediation, civil liberties and secondary enrolment. Again, we do not find any evidence of parameter heterogeneity for portfolio liabilities. To investigate if the strong evidence for parameter heterogeneity translates into a qualitatively different impact of financial openness across regimes we now turn to the partial effects.

Tables 2.2a-c report the coefficient posterior means and standard deviations for the different regimes. The detailed results of the BMA runs can be found in the appendix Tables 2.A3a-c. Table 2.2a reveals that the impact of debt flows as measured by Debt Total can actually harm the growth process under unfavorable initial conditions.[38] In particular, we find that the effect of Debt Total is negative for regimes characterized by low institutional quality (civil liberties, political rights, and investment profile) and low initial income as well as high black market premiums and high levels of fractionalization. When we compare the economic impact of Debt Total on growth across regimes, given by the posterior mean, we find that the negative impact of debt flows is strongest in countries characterized by low levels of civil liberties.[39]

In sharp contrast, once we focus on equity flows as measured by Equity Total in Table 2.2b, we find a positive and effective impact in countries characterized by low levels of corruption.[40] Surprisingly, we also find a positive effect of Equity Total for countries with initially low levels of secondary enrolment rates. This result suggests that human capital and financial openness are substitutes rather than complements in the development process and contrasts the results of Borenzstein et al. (1998).

Most striking are the results for FDI liabilities displayed in Table 2.2c. We find that FDI is an effective growth determinant under a broad set of different initial conditions. In particular, we find similar to the results for Equity Total that FDI exhibits a positive impact in sub-samples characterized by low corruption and low levels of secondary enrolment. Additionally, the impact of FDI is positive for countries characterized by high levels of bureaucratic efficiency, investment profile, initial income, trade openness and financial development. Comparing the posterior means across regimes, we find the strongest impact of FDI in countries with sufficiently low levels of corruption.

Summarizing the results so far, we have shown that once we allow the effect of financial openness to vary depending on different country characteristics, measures of financial openness are robust growth determinants even after controlling for model uncertainty with regard to alternative growth determinants. Additionally, our results highlight the importance of differentiating between different types of flows. Our

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[38] A further disaggregation of Debt Total into its components debt liabilities and debt assets did not lead to any additional insights.
[39] Note that civil liberties and political rights are measured “backwards”, i.e. high values of cl and pr imply lower levels of civil liberties and political rights, respectively.
[40] Note that low levels of corruption are indicated by high values in the ICRG corruption index.

Table 2.2: Partial Effects – Regime Approach

a) Debt Total

Threshold Variable	Post mean	Post s.d.
CL		
Lowest 75%	0.000	0.003
Highest 25%	**-4.142**	**0.772**
LnGDP		
Lowest 25%	**-2.170**	**0.977**
Highest 75%	0.030	0.129
Language		
Lowest 75%	0.000	0.000
Highest 25%	**-1.628**	**0.905**
Inv Prof		
Lowest 25%	**-1.357**	**0.725**
Highest 75%	0.046	0.116
PR		
Lowest 75%	0.000	0.000
Highest 25%	**-1.262**	**0.634**
BMP		
Lowest 75%	0.000	0.001
Highest 25%	**-1.010**	**0.723**

b) Equity Total

Threshold Variable	Post mean	Post s.d.
Corr		
Lowest 25%	-0.095	0.494
Highest 75%	**4.968**	**1.424**
Sec Enrol		
Lowest 25%	**5.374**	**3.839**
Highest 75%	0.120	0.980

c) FDI Liabilities

Threshold Variable	Post mean	Post s.d.
Corr		
Lowest 25%	0.000	0.019
Highest 75%	**7.851**	**1.494**
Inv Prof		
Lowest 25%	0.001	0.068
Highest 75%	**4.587**	**1.252**
Yrsopen		
Lowest 25%	0.104	0.747
Highest 75%	**4.750**	**1.286**
LnGDP		
Lowest 25%	-0.408	1.710
Highest 75%	**4.724**	**1.219**
Bureau		
Lowest 25%	0.394	1.267
Highest 75%	**4.620**	**1.461**
Privo		
Lowest 75%	0.981	1.735
Highest 25%	**5.945**	**2.864**
CL		
Lowest 75%	**3.639**	**2.045**
Highest 25%	-3.370	4.766
SecEnroll		
Lowest 25%	**6.498**	**3.170**
Highest 75%	1.784	1.756
EcOrg		
Lowest 25%	1.204	1.951
Highest 75%	**3.387**	**1.742**

Notes: Entries in **boldface** represent those variables that pass the effectiveness threshold (post. mean/sd >1.3). Estimates for "Highest" group are the composite mean and standard deviation.

findings suggest that debt flows can actually retard growth under a broad set of unfavorable initial conditions. In contrast, equity flows and especially FDI inflows were shown to be robust positive growth determinant. These results are in sharp contrast to Edison et al. (2002), who investigate a broad range of supportive initial conditions but do not discover any threshold effects. The main differences between their study and ours are twofold. First we include a broader set of countries (72 vs. 57). Second, Edison et al.'s interaction specifications are conditional on one specific set of control variables which seems arbitrary in the light of model uncertainty. In contrast, our results are not conditional on one particular model, but incorporate information from a broad range of potential growth models.

So far we have only allowed one threshold variable to enter the growth regression at a time. This means that, we have only investigated parts of the whole model space. However, the finding of one effective threshold might just be a manifestation of a misspecification due to the omission of other potentially relevant thresholds. In fact, this section identified a broad range of effective thresholds. In the next section we fill this gap and explicitly account for threshold uncertainty.

2.4.4 Accounting for Threshold Uncertainty

The previous results already shed light on the question about the relative importance of different thresholds by testing their robustness against a broad set of alternative linear growth models. However, we have not explicitly accounted for threshold uncertainty. In this section we address this issue directly by extending the set of possible regressors to include all interactions found to be effective in the previous section. As a result, our model space is now significantly increased and contains a variety of threshold models. The Bayesian framework is then especially suited to address the question about the relative importance of thresholds since, given the data, it provides a probability distribution over the space of all models including different threshold models. The posterior parameter distributions, in turn, take into account the probability that each of these models is the correct one.

Table 2.3: Accounting for Threshold Uncertainty

a) Debt Total

Variable	Posterior mean	Posterior s.d.
Intercept	**6.88**	**2.84**
confuc	**9.44**	**1.78**
lngdp	**-1.45**	**0.34**
corr	**0.44**	**0.14**
sub	**-1.52**	**0.47**
mining	**6.30**	**1.62**
laam	**-1.30**	**0.36**
life	**0.07**	**0.04**
yrsopen	**1.42**	**0.56**
law	-0.09	0.14
cl	0.26	0.14
ethnic	-0.70	0.77
govcons	0.00	0.01
lnbmp	-0.02	0.10
lnpopgr	-0.24	0.77
pr	0.01	0.06
oecd	-0.06	0.25
primenrol	0.00	0.00
ecorg	0.02	0.07
openk	0.00	0.00
tertenrol	0.00	0.01
invprof	0.00	0.02
kgatrstr	0.00	0.06
inflation	0.00	0.00
privo	0.04	0.23
east	0.00	0.03
lnki	0.00	0.02
language	0.00	0.00
bureau	0.00	0.02
religion	0.00	0.00
lcr100km	0.01	0.10
secenrol	0.00	0.00
priexp	0.00	0.00
debttotal	**-1.37**	**0.47**
cl75_debttotal	**-4.25**	**0.63**
invprof25_debttotal	**1.49**	**0.46**
lnbmp75_debttotal	-0.04	0.20
pr75_debttotal	0.01	0.11
language75_debttotal	0.00	0.07
lngdp25_debttotal	-0.01	0.08
No. of observations	72	

b) FDI Liabilities

Variable	Posterior mean	Posterior s.d.
Intercept	-4.04	3.82
lngdp	**-1.58**	**0.45**
confuc	**6.95**	**2.20**
lnpopgr	**-4.68**	**1.71**
sub	**-1.78**	**0.64**
life	**0.10**	**0.05**
laam	-0.65	0.59
primenrol	-0.01	0.01
east	0.33	0.60
language	0.34	0.66
corr	0.07	0.15
invprof	0.02	0.06
privo	0.06	0.29
pr	0.00	0.03
lnki	-0.01	0.11
ethnic	-0.01	0.15
secenrol	0.00	0.00
kgatrstr	-0.01	0.11
law	0.00	0.02
openk	0.00	0.00
lcr100km	0.00	0.06
cl	0.00	0.01
tertenrol	0.00	0.00
govcons	0.00	0.00
ecorg	0.00	0.01
religion	0.00	0.00
oecd	0.00	0.01
bureau	0.00	0.00
inflation	0.00	0.00
lnbmp	0.00	0.00
mining	0.00	0.00
priexp	0.00	0.00
yrsopen	0.00	0.00
fdiliab	0.00	0.21
corr25_fdiliab	**7.15**	**2.88**
lngdp25_fdiliab	0.92	2.98
secenrol25_fdiliab	-0.81	2.41
privo75_fdiliab	0.60	1.91
cl75_fdiliab	-0.41	1.64
bureau25_fdiliab	-0.13	0.70
invprof25_fdi	0.17	0.86
ecorg25_fdiliab	-0.22	1.34
yrsopen25_fdiliab	0.02	0.27
No of observations	72	

Notes: Entries in **boldface** represent those variables that pass the effectiveness threshold (post. mean/sd >1.3)

We focus on the regime approach in this section since it yielded the richest set of different threshold effects. We also focus on FDI liabilities as well as Debt Total, since these measures revealed the greatest evidence of thresholds uncertainty. For computational reasons we only include those interactions that have been found effective in the previous section. The results displayed in Tables 2.3a, b show a clear picture. After controlling for model uncertainty with respect to different initial conditions the number of effective interactions terms is significantly reduced. Specifically, for the case of Debt Total the only thresholds with a posterior mean/sd ratio greater 1.3 are a measure of political institutions (civil liberties) and property rights (investment profile). For FDI liabilities the only effective threshold is corruption. This finding is especially remarkable since we tested this threshold against 8 alternative thresholds, covering initial GDP, trade openness, financial intermediation, human capital and other institutional variables. Taken together, the results of Tables 2.3a and b reveal that the data clearly favors institutional thresholds over other potential thresholds.

The results of this section have several significant implications. Our findings highlight the importance to account for model uncertainty with respect to different thresholds. While we found a large number of threshold variables effective in the previous section, this section shows that once we explicitly take into account threshold uncertainty this number is significantly reduced. Thus, we conclude that studies that only investigate the importance of one specific threshold without taking into account other equally well justified thresholds, reach conclusions that underestimate the uncertainty surrounding the model selection. Further, while a large body of literature address the direct effects of institutions on long term growth, our results emphasize the view that an important channel through which institutions might effect growth is by influencing the growth impact of external capital flows.

To offer some possible interpretations of our results, our finding that debt flows are associated with decreased growth in countries lacking sound political institutions and property rights can be interpreted in line with the theoretical model of Bussiere, Fratzscher and Koeniger (2006). Their model predicts that the debt structure is tilted towards short term debt in countries facing uncertainty about investment returns. Dependency on short term debt, in turn, is typically associated with a higher probability of financial crisis (e.g. Chang and Velasco, 2000). Further, several studies suggest that the level of corruption is negatively correlated with the level of FDI inflows (e.g. Egger and Winner, 2006; Wei 2000a, b). Additionally, our results lend support to the view that the level of corruption might also impact the quality of FDI. For instance, Smarzynska and Wei (2000) show, using firm level data, that technological more advanced firms are discouraged to form joint ventures in a highly corrupt host country.

2.5 Conclusions

The fact that most highly developed countries are closely integrated into the global financial markets together with strong theoretical predictions that financial openness creates welfare benefits, has for a long time led to the presumption that developing countries should embrace financial globalization. However, the recent experiences of financial crises together with the inconclusiveness of empirical work have cast doubt over these predictions. Recent research has offered a promising route to reconcile these findings. It stresses that premature opening of the capital account in the absence of some basic supporting conditions can delay growth benefits. In this paper we have provided a comprehensive analysis of threshold effects investigating a broad range of potential supportive conditions. A key methodological innovation was the use of Bayesian Model Averaging techniques to appropriately account for model uncertainty that has plagued much of the growth research but has been neglected by the financial openness literature.

Our results provided substantial evidence of the relevance of threshold effects. Once we allowed the marginal effect of our measures of financial openness to vary across countries depending on specific country conditions, we found that financial integration indeed constitutes a robust growth determinant for sub-groups of countries. Our results, however, also highlighted the differential impact of different types of flows. We found that debt flows are negatively correlated with long term growth in countries with unfavorable initial conditions, while especially FDI is associated with positive growth in countries meeting certain supportive conditions. Important was also our finding that once we explicitly account for uncertainty about the nature of the threshold, the number of effective thresholds was significantly reduced and we found exclusively institutional thresholds to matter. Specifically, our results suggest that corruption is the crucial threshold for FDI inflows while a combination of both strong political institutions and property rights are necessary to avert the risks of debt flows. Although, more theoretical work along with evidence from micro-level studies is warranted to better understand the exact channels through which institutions affect the growth outcomes of financial integration, our results clearly indicate a policy priority for improving institutions to both benefit from financial integration and avert the possible risks.

Appendix Chapter 2

Table 2.A1: Variable Definitions

Theory	Variable Name	Description	Source
Dependent Variable	grgdpch	Average growth rate of real GDP per capita over the period 1980-2000	Penn World Tables (PWT) 6.2
Solow	lngdp	Logarithm of real GDP p.c. in 1980	PWT 6.2
	lnki	Log of average investment share in real GDP over period 1980-2000	PWT 6.2
	lnpopgr	Log of average population growth rates +0.05 over period 1980-2000	PWT 6.2
Human Capital	life	Life expectancy at birth in 1980	World Development Indicators (WDI)
	primenrol	Primary gross enrolment rate, 1980	World Bank/Unesco
	secenrol	Secondary gross enrolment rate, 1980	World Bank/Unesco
	tertenrol	Tertiary gross enrolment rate, 1980	World Bank/Unesco
Political Institutions	cl	Civil liberties, 1980	Freedom House
	pr	Political rights, 1980	Freedom House
	ecorg	Degree of capitalism index	Hall and Jones (1999)
Economic Institutions	corr	Corruption, average 1984-86	ICRG
	law	Law&Order, average 1984-86	ICRG
	bureau	Bureaucratic quality, avg. 1984-86	ICRG
	invprof	Investment profile (avg. of 3 subcomponents: risk of contract viability/expropriation, profit repatriation and payment delays), avg. 84-86	ICRG
Geography and Endowments	kgatrstr	% land area in Koeppen-Geiger tropics and subtropics	Center for International Development (CID)
	lcr100km	% land area within 100 km of ice-free coast	ibid
	mining	Fraction of mining in GDP	Hall and Jones (1999)
	priexp	Fraction of primary exports in total exports in 1970	Sachs and Warner(1995)
Fractionalization	ethnic	Prob. that 2 randomly selected people belong to different ethnic groups	Alesina et al. (2003)
	language	Prob. that 2 randomly selected people belong to different linguistic groups	Alesina et al. (2003)
	religion	Prob. that 2 randomly selected people belong to different religious groups	Alesina et al. (2003)
Macro Policies	openk	Exports plus imports / GDP, avg. 80-85	PWT 6.2
	yrsopen	Number of years open between 1959-1994	Sachs and Warner(1995)
	inflation	Inflation, CPI, average 1980-85	WDI
	lnbmp	ln(1+average black market premium over period 1980-85)	Global Development Network Growth Database (GDNGD)
	govcons	Avg. government consumption expenditure as % GDP over period 1980-85	WDI
Regional Heterogeneity	east	East and southeast asia dummy	GDNGD
	laam	Latin america dummy	GDNGD
	sub	Sub saharan africa dummy	GDNGD
	oecd	Dummy for OECD countries	OECD
	confuc	Fraction of population confucian	Barro (1999)
Domestic Financial Development	privo	Private credit by deposit money banks and other financial institutions / GDP, avg. 80-85	Beck, Demirgüç-Kunt and Levine (2000)
Financial Openness	Total	Total assets and liabilities / GDP, avg. 80-85	Lane and Milesi-Ferretti (2006)
	Equity Total	Portfolio equity and FDI assets and liabilities / GDP, avg. 80-85	ibid
	Debt Total	Debt assets and liabilities / GDP, avg. 80-85	ibid
	FDIliab	FDI liabilities / GDP, avg. 80-85	ibid
	Portliab	Portfolio equity liabilities / GDP, avg. 80-85	ibid

Table 2.A2: BMA Results - Continuous Interactions Approach

	(1)		(2)		(3)		(4)		(5)		(6)		(7)	
Variable	**a)**	**b)**	**a)**	**b)**	**a)**	**b)**	**a)**	**b)**	**a)**	**b)**	**a)**	**b)**	**a)**	**b)**
Intercept	-0.74	4.65	1.37	4.84	1.82	5.36	1.13	5.21	1.24	4.60	0.71	4.92	-1.38	5.41
lngdp	**-1.78**	**0.48**	**-1.61**	**0.46**	**-1.59**	**0.49**	**-1.71**	**0.50**	**-1.75**	**0.45**	**-1.22**	**0.64**	**-1.45**	**0.59**
lnpopgr	**-3.93**	**1.73**	**-4.01**	**1.82**	**-3.41**	**2.06**	**-3.73**	**1.98**	**-4.18**	**1.67**	**-3.55**	**2.14**	**-3.72**	**1.92**
confuc	**6.30**	**2.87**	**5.95**	**2.81**	**6.58**	**2.93**	**6.51**	**2.90**	**6.66**	**2.64**	**6.48**	**2.95**	**6.83**	**3.07**
sub	**-1.57**	**0.81**	**-1.69**	**0.78**	**-1.66**	**0.79**	**-1.69**	**0.78**	**-2.03**	**0.65**	**-1.50**	**0.76**	**-1.59**	**0.85**
east	1.13	0.91	**1.55**	**0.87**	**1.63**	**0.90**	**1.47**	**0.96**	**1.39**	**0.98**	0.89	1.00	**1.41**	**0.95**
life	**0.11**	**0.05**	0.07	0.06	0.08	0.06	**0.09**	**0.06**	0.07	0.06	0.03	0.06	0.07	0.06
corr	0.19	0.20	0.02	0.07	0.19	0.20	0.19	0.21	**0.28**	**0.20**	0.11	0.18	**0.32**	**0.21**
kgatrstr	-0.56	0.71	**-1.31**	**0.71**	**-1.35**	**0.77**	**-1.13**	**0.83**	-0.86	0.86	-0.76	0.86	-0.63	0.83
pr	-0.06	0.12	**-0.22**	**0.15**	**-0.22**	**0.15**	-0.17	0.16	-0.13	0.15	-0.16	0.17	-0.11	0.16
language	0.33	0.67	0.15	0.47	0.50	0.78	0.45	0.76	0.27	0.60	0.22	0.58	0.91	0.96
secenrol	0.00	0.01	0.00	0.01	0.00	0.01	0.00	0.01	0.00	0.01	0.00	0.01	0.00	0.01
mining	0.00	0.09	0.00	0.00	0.26	1.35	0.26	1.36	0.03	0.41	0.28	1.34	0.93	2.27
laam	-0.05	0.24	-0.13	0.41	-0.09	0.35	-0.11	0.39	-0.03	0.19	-0.30	0.62	-0.14	0.41
invprof	0.03	0.08	0.07	0.11	0.04	0.10	0.03	0.08	0.00	0.02	0.10	0.14	0.03	0.08
lnki	-0.10	0.36	-0.19	0.47	-0.28	0.58	-0.30	0.59	-0.27	0.57	-0.13	0.43	-0.14	0.43
primenrol	-0.01	0.01	0.00	0.01	0.00	0.01	0.00	0.01	0.00	0.01	0.00	0.00	0.00	0.01
lcr100km	-0.01	0.09	-0.01	0.09	-0.02	0.18	-0.02	0.15	-0.02	0.16	-0.01	0.14	-0.04	0.23
tertenrol	0.00	0.00	0.00	0.01	0.00	0.01	0.00	0.01	0.00	0.01	0.00	0.01	0.00	0.01
oecd	0.00	0.04	-0.06	0.26	-0.05	0.25	-0.02	0.14	-0.02	0.13	-0.13	0.40	-0.02	0.17
bureau	0.00	0.01	0.03	0.11	0.01	0.07	0.03	0.12	0.03	0.11	0.05	0.15	0.01	0.07
openk	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
inflation	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
cl	0.00	0.01	0.00	0.03	0.00	0.00	0.00	0.02	0.00	0.02	0.00	0.00	0.00	0.04
ethnic	-0.21	0.63	-0.06	0.38	-0.07	0.42	-0.09	0.47	-0.14	0.49	-0.48	0.97	-0.01	0.13
govcons	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00
priexp	0.00	0.03	0.00	0.03	0.00	0.03	0.00	0.04	0.00	0.02	0.00	0.03	0.00	0.08
privo	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.15	0.00	0.00	0.00	0.00
religion	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
law	0.00	0.01	0.00	0.00	0.00	0.01	-0.03	0.10	0.00	0.01	0.00	0.00	0.00	0.00
lnbmp	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
ecorg	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.03	0.00	0.00	0.00	0.00
yrsopen	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.09	-0.02	0.19	0.00	0.01
fdiliab	0.07	0.55	0.03	0.81	0.35	1.20	0.40	1.28	-3.96	4.96	0.73	1.64	**8.09**	**3.95**
bureau_fdi	**1.79**	**0.54**												
corr_fdi			**1.37**	**0.45**										
ecorg_fdi					**0.81**	**0.41**								
law_fdi							**0.95**	**0.50**						
invprof_fdi									**1.31**	**0.75**				
yrsopen_fdi											**7.25**	**4.41**		
ethnic_fdi													**-10.48**	**7.57**
No. of obs.	72		72		72		72		72		72		72	

Notes: a) Posterior mean; b) Posterior standard deviation.
Entries in **boldface** represent those variables that pass the effectiveness threshold (post. mean/sd >1.3).
Only those results are reported for which the interaction term exceeds the effectiveness threshold.

Table 2.A3: BMA Results – Regime Approach

a) Debt Total

	(1)		(2)		(3)		(4)		(5)		(6)	
Variable	**a)**	**b)**	**a)**	**b)**	**a)**	**b)**	**a)**	**b)**	**a)**	**b)**	**a)**	**b)**
Intercept	**5.31**	**2.64**	0.18	4.79	-1.92	4.93	-1.83	4.61	-2.64	4.63	-1.76	4.85
lngdp	**-1.57**	**0.36**	**-2.35**	**0.52**	**-1.55**	**0.51**	**-1.75**	**0.56**	**-1.85**	**0.44**	**-1.89**	**0.49**
lnpopgr	-0.05	0.38	**-4.42**	**1.73**	**-3.31**	**2.09**	**-3.72**	**1.99**	**-4.70**	**1.67**	**-3.68**	**1.88**
life	**0.11**	**0.03**	**0.14**	**0.05**	**0.14**	**0.06**	**0.13**	**0.06**	**0.14**	**0.05**	**0.17**	**0.05**
confuc	**10.80**	**1.89**	**6.41**	**3.05**	**5.00**	**3.53**	**7.12**	**2.55**	**5.83**	**2.65**	**7.15**	**2.66**
sub	**-1.64**	**0.50**	-0.97	0.91	-0.30	0.68	**-1.45**	**0.77**	**-1.34**	**0.72**	**-1.26**	**0.84**
mining	**4.67**	**1.92**	**3.52**	**2.98**	1.86	2.84	**4.95**	**2.86**	**6.36**	**2.21**	**6.21**	**2.39**
corr	**0.52**	**0.13**	0.25	0.22	0.03	0.11	0.22	0.23	0.05	0.14	0.25	0.21
east	0.01	0.12	0.68	0.86	**1.63**	**0.81**	0.32	0.64	0.95	0.90	0.60	0.80
primenrol	0.00	0.00	-0.01	0.01	-0.01	0.01	-0.01	0.01	**-0.02**	**0.01**	**-0.02**	**0.01**
laam	**-1.30**	**0.39**	-0.16	0.43	-0.14	0.42	-0.12	0.39	-0.07	0.31	-0.03	0.21
openk	**0.01**	**0.00**	0.00	0.01	0.01	0.01	0.01	0.01	0.00	0.00	0.00	0.00
language	0.02	0.16	0.80	0.94	0.75	0.95	0.38	0.70	0.09	0.39	0.25	0.60
kgatrstr	-0.01	0.08	-0.69	0.76	-0.61	0.77	-0.07	0.28	-0.39	0.65	-0.05	0.29
bureau	0.00	0.00	0.02	0.09	0.14	0.21	0.17	0.25	0.10	0.18	0.04	0.13
cl	**0.23**	**0.16**	-0.01	0.04	-0.05	0.12	0.00	0.00	0.00	0.03	0.00	0.03
ecorg	0.01	0.03	0.02	0.07	0.00	0.03	0.03	0.08	0.08	0.14	0.01	0.04
ethnic	-0.12	0.40	-0.01	0.15	-0.15	0.57	-0.04	0.31	-0.04	0.28	-0.02	0.23
govcons	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.02	0.00	0.02	0.00	0.01
inflation	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
invprof	0.02	0.06	0.07	0.12	0.01	0.05	0.00	0.03	0.00	0.04	0.00	0.03
law	-0.02	0.07	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02
lcr100km	0.00	0.03	0.01	0.13	0.00	0.00	0.00	0.04	0.01	0.09	0.00	0.02
lnbmp	-0.02	0.11	0.00	0.06	-0.02	0.14	-0.01	0.08	0.00	0.03	0.00	0.00
lnki	0.00	0.04	-0.03	0.20	-0.12	0.40	-0.04	0.25	-0.15	0.43	-0.11	0.38
oecd	0.00	0.01	-0.02	0.16	0.00	0.01	0.00	0.07	-0.07	0.32	0.00	0.05
privo	0.15	0.44	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00
pr	0.00	0.03	-0.10	0.14	-0.06	0.12	0.00	0.02	-0.06	0.12	-0.05	0.10
priexp	0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01
religion	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.00	0.00
secenrol	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00
tertenrol	0.00	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
yrsopen	0.32	0.52	0.00	0.00	0.00	0.01	0.04	0.23	0.17	0.47	0.03	0.20
debttotal	0.00	0.00	**-2.17**	**0.98**	0.00	0.00	0.00	0.00	**-1.36**	**0.73**	0.00	0.00
cl75_debttotal	**-4.14**	**0.72**										
lngdp25_debttotal			**2.20**	**0.99**								
language75_debttotal					**-1.63**	**0.91**						
pr75_debttotal							**-1.26**	**0.63**				
invprof25_debttotal									**1.40**	**0.73**		
lnbmp75_debttotal											**-1.01**	**0.72**
No. of obs.	72		72		72		72		72		72	

Notes: a) Posterior mean; b) Posterior standard deviation.
Entries in **boldface** represent those variables that pass the effectiveness threshold (post. mean/sd >1.3).
Only those results are reported for which the interaction term exceeds the effectiveness threshold.

b) Equity Total

Variable	(1) a)	(1) b)	(2) a)	(2) b)
Intercept	-2.50	4.27	-3.25	4.85
lngdp	**-1.70**	**0.44**	**-1.90**	**0.47**
lnpopgr	**-4.31**	**1.90**	**-4.12**	**2.02**
life	**0.11**	**0.05**	**0.14**	**0.05**
confuc	**6.52**	**2.52**	**6.87**	**2.78**
sub	**-1.54**	**0.68**	**-1.95**	**0.88**
corr	0.01	0.05	**0.34**	**0.21**
primenrol	-0.01	0.01	-0.01	0.01
east	0.50	0.73	0.61	0.82
mining	0.50	1.49	1.58	2.91
language	0.01	0.11	0.79	0.90
laam	-0.42	0.59	-0.28	0.54
bureau	0.02	0.08	0.04	0.14
cl	0.00	0.00	0.00	0.01
ecorg	0.00	0.01	0.00	0.03
ethnic	-0.02	0.22	-0.07	0.37
govcons	0.00	0.00	0.00	0.01
inflation	0.00	0.00	0.00	0.00
invprof	0.03	0.08	0.00	0.00
kgatrstr	-0.08	0.30	-0.15	0.43
law	0.00	0.00	-0.01	0.05
lcr100km	0.00	0.06	0.00	0.05
lnbmp	0.00	0.00	0.00	0.00
lnki	-0.01	0.13	-0.06	0.30
oecd	0.00	0.03	-0.01	0.12
openk	0.00	0.00	0.00	0.00
privo	0.00	0.00	0.02	0.16
pr	-0.02	0.07	-0.01	0.06
priexp	0.00	0.00	0.00	0.01
religion	0.00	0.00	0.00	0.00
secenrol	0.00	0.01	0.00	0.00
tertenrol	0.00	0.00	0.00	0.01
yrsopen	0.00	0.00	0.00	0.00
eqtotal	-0.10	0.49	**5.37**	**3.84**
corr25_eqtotal	**5.06**	**1.45**		
secenrol25_eqtotal			**-5.25**	**3.82**
No. of obs.	72		72	

Notes: a) Posterior mean; b) Posterior standard deviation. Entries in **boldface** represent those variables that pass the effectiveness threshold (post. mean/sd >1.3). Only those results are reported for which the interaction term exceeds the effectiveness threshold.

c) FDI Liabilities

	(1)		(2)		(3)		(4)		(5)		(6)		(7)		(8)	
Variable	**(a)**	**(b)**	**(a)**	**(b)**	**(a)**	**(b)**	**(a)**	**(b)**	**(a)**	**(b)**	**(a)**	**(b)**	**(a)**	**(b)**	**(a)**	**(b)**
Intercept	-4.20	3.90	2.92	4.66	2.73	4.78	3.98	5.04	0.49	4.91	-1.54	5.28	2.32	5.44	-0.99	5.32
lngdp	**-1.53**	**0.39**	**-1.77**	**0.46**	**-1.24**	**0.56**	**-1.80**	**0.45**	**-1.74**	**0.50**	**-1.69**	**0.48**	**-1.38**	**0.59**	**-1.85**	**0.47**
lnpopgr	**-4.66**	**1.72**	**-3.98**	**1.75**	**-3.32**	**2.10**	**-3.42**	**1.89**	**-3.39**	**1.93**	**-4.55**	**1.75**	-2.16	2.26	**-3.73**	**2.09**
life	**0.10**	**0.05**	0.07	0.06	0.01	0.03	0.07	0.06	**0.10**	**0.05**	**0.10**	**0.07**	0.08	0.07	**0.12**	**0.05**
confuc	**6.87**	**2.22**	**6.01**	**2.87**	**6.22**	**2.77**	**6.60**	**2.82**	**6.97**	**2.87**	**7.12**	**2.61**	**7.42**	**2.84**	**6.98**	**2.69**
sub	**-1.73**	**0.63**	**-1.83**	**0.67**	**-1.87**	**0.64**	**-1.67**	**0.74**	**-1.77**	**0.83**	**-1.47**	**0.73**	**-1.76**	**0.80**	**-2.07**	**0.80**
corr	0.03	0.09	0.13	0.18	0.13	0.19	0.23	0.20	**0.33**	**0.20**	0.09	0.16	**0.40**	**0.23**	**0.35**	**0.20**
east	0.41	0.66	**1.76**	**0.80**	1.14	0.93	**1.85**	**0.73**	1.03	0.98	0.96	0.98	0.95	1.04	0.98	0.99
kgatrstr	-0.02	0.18	**-1.50**	**0.64**	-1.00	0.80	**-1.69**	**0.57**	-0.66	0.79	-0.77	0.88	-0.66	0.83	-0.56	0.81
pr	-0.01	0.04	**-0.25**	**0.15**	-0.23	0.17	**-0.27**	**0.12**	-0.07	0.13	-0.20	0.17	-0.07	0.13	-0.07	0.14
language	0.23	0.55	0.24	0.56	0.10	0.39	0.70	0.85	1.02	0.98	0.24	0.59	1.09	1.00	0.76	0.88
laam	-0.65	0.59	-0.06	0.30	-0.52	0.79	-0.02	0.18	-0.03	0.18	-0.07	0.29	1.10	2.50	-0.33	0.58
bureau	0.00	0.03	0.12	0.21	0.03	0.11	0.02	0.08	0.00	0.03	0.03	0.11	0.02	0.09	0.02	0.09
cl	0.00	0.01	0.00	0.00	0.00	0.01	0.00	0.02	0.00	0.02	0.00	0.00	0.00	0.01	0.00	0.02
ecorg	0.00	0.00	0.01	0.06	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00
ethnic	0.00	0.02	-0.04	0.29	-0.12	0.50	-0.11	0.46	-0.56	0.99	-0.04	0.31	-0.68	1.09	-0.05	0.32
govcons	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.01	0.03	0.00	0.02
inflation	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
invprof	0.02	0.07	0.00	0.02	0.12	0.14	0.10	0.13	0.03	0.08	0.07	0.12	0.03	0.08	0.01	0.05
law	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.00	0.01	0.00	0.00	-0.38	0.62	0.00	0.04
lcr100km	-0.01	0.10	-0.03	0.21	0.00	0.07	-0.01	0.11	-0.02	0.15	-0.01	0.10	-0.01	0.06	-0.02	0.14
lnbmp	0.00	0.00	0.03	0.17	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.03	0.21	0.00	0.05
lnki	-0.04	0.21	-0.30	0.58	-0.08	0.31	-0.31	0.58	-0.15	0.44	-0.19	0.49	0.00	0.00	-0.18	0.48
mining	0.00	0.00	0.12	0.77	0.00	0.00	0.01	0.22	0.09	0.73	2.98	3.31	-0.17	0.47	0.57	1.92
oecd	0.00	0.00	-0.07	0.31	-0.18	0.45	-0.04	0.21	0.00	0.07	-0.02	0.15	-0.03	0.20	-0.01	0.13
openk	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00
privo	0.06	0.31	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.00
priexp	0.00	0.00	0.00	0.01	0.00	0.05	0.00	0.08	0.00	0.04	0.00	0.01	0.00	0.00	0.00	0.03
primenrol	-0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.01	0.01	0.00	0.01	0.00	0.01
religion	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.12	0.00	0.00	0.00	0.00
secenrol	0.00	0.00	0.00	0.01	0.00	0.01	-0.01	0.01	0.00	0.01	-0.01	0.01	0.00	0.01	0.00	0.01
tertenrol	0.00	0.00	0.00	0.01	0.00	0.01	0.00	0.01	0.00	0.01	0.00	0.01	-0.01	0.02	0.00	0.01
yrsopen	0.00	0.00	0.00	0.08	0.00	0.00	0.00	0.03	0.03	0.19	0.00	0.00	0.06	0.28	0.00	0.00
fdiliab	0.00	0.02	0.00	0.07	0.10	0.75	-0.41	1.71	0.39	1.27	0.98	1.73	**3.64**	**2.05**	**6.50**	**3.17**
corr25_fdiliab	**7.85**	**1.49**														
invprof25_fdiliab			**4.59**	**1.26**												
yrsopen25_fdiliab					**4.65**	**1.50**										
lngdp25_fdiliab							**5.13**	**2.04**								
bureau25_fdiliab									**4.23**	**1.96**						
privo75_fdiliab											**4.96**	**3.02**				
cl75_fdiliab													**-7.01**	**5.15**		
secenrol25_fdiliab															**-4.71**	**3.46**
No. of obs.	72		72		72		72		72		72		72		72	

Notes: a) Posterior mean; b) Posterior standard deviation.
Entries in **boldface** represent those variables that pass the effectiveness threshold (post. mean/sd >1.3).
Only those results are reported for which the interaction term exceeds the effectiveness threshold.

References Chapter 2

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3 Sources of the German Productivity Demise

Tracing the Effects of Industry-Level ICT Investment

3.1 Introduction

US Labor productivity growth increased remarkably after 1995 and accelerated again after 2000. Stiroh (2006) highlights these dual productivity surges which have been extensively analyzed in Jorgenson, Ho, Samuels and Stiroh (2006). In sharp contrast, we show that German labor productivity growth experienced two successive productivity *decelerations* in the same time periods. Figure 3.1a plots labor productivity growth from 1991 to 2004 and highlights how US productivity growth outpaced Germany's. While average labor productivity (ALP) growth slowed from 2.4 percent to 2.0 percent in Germany after 1995, it surged from 1.5 percent to 2.5 percent in the US. The productivity gap widened further when US productivity growth rose again by 0.8 percent after 2000, whereas Germany's dropped another 0.7 percent. The divergence is not an artifact of the choice of trend breaks. Figure 3.1b plots the US and German productivity trends to document the secular divergence. Not only is Germany's absolute decline worrisome, but its decline relative to the US also signals a departure from the technology frontier.

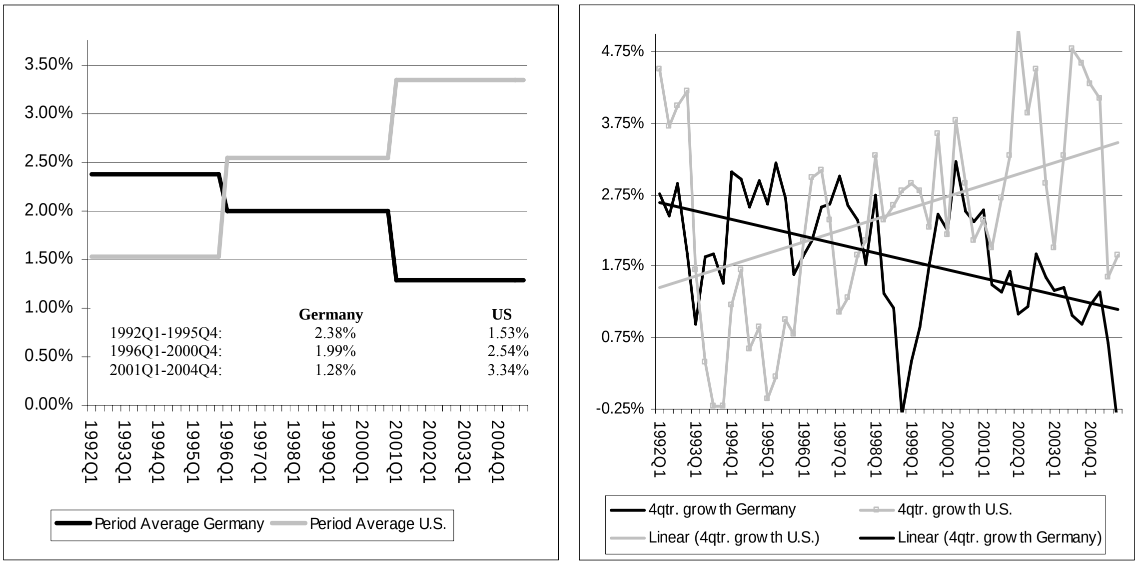
We analyze the sources of Germany's productivity demise using a new database that allows industry-level comparisons with the US. The novelty of the Röhn et al. (2007) *ifo industry growth accounting database* is its detailed information on 12 investment assets for 52 German industries, a level of detail not provided by official German statistics. Röhn et al. derive the database from the *ifo investment database (Investorenrechung)* which gathers investment micro data on over 100 assets for 52 German industries and aggregates them to 12 major industry investments (see Röhn et al., 2007, for details). Röhn et al. (2007) calculate capital stocks and services, which then allows for the first analysis of productivity and Information and Communication Technology (ICT) contributions to aggregate German productivity at the 52-industries level.

A broad consensus attributes the first productivity surge in the US to ICT investment, much of it originating in ICT-Intensive industries.[41] US productivity growth was positively affected by ICT capital deepening, technological

[41] Jorgenson and Stiroh (2000), Oliner and Sichel (2000), Stiroh (2002), Jorgenson, Ho and Stiroh (2005a).

Figure 3.1: Labor Productivity Growth: U.S. vs. Germany

a) Period average labor productivity growth **b) 4-quarter labor productivity growth**



Sources: US is Nonfarm Business Sector (US Bureau of Labor Statistics), Germany: Total Economy (DeStatis).

advancements in ICT-Producing industries, and productivity gains in ICT-Using industries; we investigate whether these dynamics can also be observed in German industries. To date, the evidence on the industry-level sources of Germany's productivity decline is scarce, especially for the post 2000 slowdown. As Figure 3.1a suggests, however, this second productivity decline was even more pronounced than the first. Therefore, we pay special attention to the sources of both productivity slowdowns and dissect the German productivity demise into its proximate causes. We also identify the specific industries that represented the largest drag on German productivity and those whose performance mitigated the aggregate productivity slowdowns.

Our results show that while the first productivity surge in the US was driven by ICT, the post 1995 productivity decline in Germany was driven by a collapse in both the Non-ICT capital deepening and the Non-ICT industries' total factor productivity (TFP) growth. German ICT-Intensive industries' ICT investment and TFP surged 1995-2000, but not to the extent observed in the US. ICT capital deepening in Germany was only one third of the level reached in the US. Therefore, the emergent German information sector was not sufficiently strong to offset productivity losses in other industries.

The second productivity surge in the US after 2000 was not solely driven by ICT. Instead, ICT capital deepening and ICT-Producing industries' TFP growth declined and TFP growth in Non-ICT-Producing industries became the primary driving force.[42] The same decline in ICT capital deepening and TFP growth can be observed in Germany after 2000. However, the decisive difference between the US and Germany's productivity performance was that productivity in Non-ICT-Producing industries did not pick up, but instead collapsed in Germany. 28 out of 52 industries accounting for almost 50 percent of aggregate value added experienced negative TFP growth post 2000.

The remarkable impact of ICT investment on growth and productivity in the US has spurred interest in uncovering the effects of ICT across countries. Colecchia and Schreyer (2002) collect ICT investment data from national sources for nine OECD countries to find that their ICT investment contribution to growth was considerably smaller than in the US. Focusing on the European slowdown in the mid nineties, Timmer, Ypma and van Ark (2003) emphasize that slower ICT capital deepening and TFP growth in ICT-Producing industries were only one part of the story. Declining rates of Non-ICT capital deepening and flat TFP growth in most other industries were equally important in explaining the diverging productivity trends between the U.S and Europe. Several studies use industry-level data to suggest that most of the difference in ALP growth between the US and Europe, Canada, Japan, and Germany can be traced back to a few ICT-intensive service industries, especially trade and finance.[43] These industries are also thought to be largely responsible for the higher rates of ICT capital deepening and TFP growth outside ICT production in the US (see Inklaar, O'Mahony and Timmer, 2005).

Our data shows that only six German industries, with 12 percent of total value added, saw labor productivity increases post 1995 and post 2000. The largest rise occurred in Wholesale Trade and Construction. More than twice as many industries (13 industries), with almost twice the share in total value added (21 percent), experienced successive declines, however, featuring prominently Machinery and the

[42] See Stiroh and Botsch (2007), Jorgenson, Ho and Stiroh (2006), van Ark and Inklaar (2005) and Jorgenson, Ho, Samuels and Stiroh (2006).

[43] See van Ark, Inklaar and McGuckin (2003a, b) and van Ark, and Inklaar (2003).

Chemicals manufacturing. Most remarkable, however, is our finding that the number of industries that contribute negatively to German labor productivity has been increasing over time. Between 1991 and 1995, fourteen industries contributed negatively; after 2000, however, over 40 percent of German industries (21 of the 52 industries) constituted a drag on the nation's aggregate labor productivity.

3.2 Data

To base our analysis on consistent data, we focus exclusively on Unified Germany (post 1990). For our industry-level analysis, we collect data on value added, investment, capital stocks and services, and quality adjusted labor hours for 52 German industries and 12 different assets from 1991 to 2003. For a detailed description of the data we refer the interested reader to Tables A1 and A2 in Röhn et al. (2007). The 52 industries span the entire German economy (with the exception of household services which constituted only a 0.3 percent value added share in 2004). The German Statistical Office (DeStatis) provides value added, labor hours, and labor compensation by industry.[44] Estimates of labor quality growth are taken from the Groningen Growth Accounting Database (Inklaar, O'Mahony and Timmer, 2005).[45]

The *ifo industry growth accounting database* (Röhn et al., 2007) is our source for capital data. It provides industry-level time series on 13 different investments, capital stocks and capital services for West Germany for the period 1970-1990 in the older WZ79 classification of DeStatis. From 1991 to 2003 Röhn et al. provide 12 different investments, capital stocks and capital services for Unified Germany at the two digit industry-level NACE classification using the ownership concept. The *ifo industry growth accounting database* has three unique features. First, it provides information on an unusually large number of capital stocks and capital services at the industry level. Second, the industry-level assets include three different ICT assets (computer and office equipment, communication equipment and software), which are of particular interest to understand the productivity performance of industries in the

[44] DeStatis provides labor hours for 14 broad industries only; to obtain estimates for our set of industries, we multiplied the DeStatis hours/worker ratios by workers in each sub-sector.
[45] Inklaar et al. (2005) provide labor quality until 2000. We use 1980-2000 data to extrapolate labor quality to 2003 using an AR process with optimal lag length (using the AIC, Final Prediction Error, Hannan-Quinn and Schwarz criterion) for each industry to match the post 2000 aggregate labor quality growth provided by Schwerdt and Turunen (2007).

past decade. Third, the detailed disaggregation of the different asset types and marginal productivities (measured as user costs) allows us to construct the most accurate measures of ICT and Non-ICT capital services.

To deflate ICT assets into constant-quality units, Röhn et al. (2007) employ the deflators for computer and office equipment, communication equipment and software developed by Timmer, Ypma and van Ark (2003) and Schreyer (2002). These deflators are based on US hedonic price indices and are adjusted for differences in general inflation levels between Germany and the US. For other assets the DeStatis deflators are applied. We obtain measures for ICT and Non-ICT capital services by using Tornqvist aggregation with user costs of capital as flexible weights.

The *ifo industry growth accounting database* allows us to separate industries into ICT-Producing, ICT-Using, and Non-ICT (or "Other") industries. A broad US literature has established categories for ICT-Intensive and Non-ICT-Intensive industries by using the shares of ICT capital in total capital services.[46] To further differentiate ICT-Intensive industries into ICT-Using and ICT-Producing, the literature follows the lead of the US Bureau of Economic Analysis ICT-Producing industry definition. ICT-Using industries constitute the residual group.

Subsequent papers that examine the effects of ICT-Intensive industries in the EU or other countries customarily adopt US definitions (e.g. van Ark, Inklaar, McGuckin, 2003a, b; O'Mahony and van Ark, 2003). That is, if an industry is ICT-Using by US standards, it is also assumed to be ICT-Using in the comparison country. This does not take into account that the same industries in other countries may have very different ICT intensities. In addition, exact correspondences between US and other nations' industry classifications may not exist. The *ifo industry growth accounting database* contains unique ICT investment and capital stock data that allows us to develop an ICT industry classification scheme which uses the definitions introduced by the previous literature, but employs German data to draw distinctions. Therefore, we provide the first German industry-based categorization of industries into ICT-Intensive and Non-ICT-Intensive. We use Stiroh's (2002, 2006) definition for ICT-Intensive industries (those whose ICT shares exceed the median). To sepa-

[46] See, for example, Stiroh (2002, 2006), Jorgenson, Ho, Stiroh (2005b), Bailey and Lawrence (2001), and Triplett and Bosworth (2004).

rate ICT-Producing industries from ICT-Intensive industries, we adopt the DeStatis (2006) definition and classify the following industries as ICT-Producing: Office Machinery and Computers (NACE 30); Radio, TV and Communication Equipment (NACE 32); Instruments (NACE 33); Communication Services (NACE 64) and Computer and Related Services (NACE 72).[47]

A similar productivity database exists at the Groningen Growth and Development Centre, which focuses on international productivity comparisons. Differences between the *ifo industry growth accounting database* and the *Groningen Industry Growth Accounting Database* are fourfold. First, Groningen reports 26 industries, while Röhn et al. (2007) report data for 52 industries. Second, ICT assets are said to include computers and peripherals, software and communication equipment. Röhn et al include office equipment in ICT assets, since office equipment and computers cannot be separated at the German industry-level. A third difference arises in the asset class entitled "buildings and structures." Our data includes residential and non-residential buildings and structures while Groningen includes only non-residential buildings and structures. A breakdown into residential and non-residential buildings on the industry-level is not provided by DeStatis.

Finally, and perhaps most importantly, since German software investments are not reported by DeStatis, the Groningen database assumes that a fixed fraction of intangible assets is software. Groningen then generates German industry-level software investment by using a ratio of software to IT-equipment investment that was obtained from an average of French, Dutch and US data. Instead, the ifo productivity database obtains data on software investment shares in total intangible assets, and industry-level software investment from a study (Herrmann and Müller, 1997) and surveys conducted by the *ifo Investment Survey*.[48] As detailed in Hermann and Müller (1997) the software estimates are based on specific questions that solicited information on industry level investment in purchased and own account software in 1995, 1998, 1999 and 2000.

[47] For a full list of our ICT-classification scheme for the 52 industries, compare Table 3.A1 in the appendix.
[48] The *ifo Investment Survey* follows the EU guidelines for harmonized business surveys and contains 70,000 German firms, 5000 of which are surveyed for each sample period. It is established as an excellent leading indicator of German investment; it is also incorporated in a number of other leading indicators, most prominently the European Commission's *Economic Indicators of the Euro Zone*.

3.3 Deriving Industry Contributions to Labor Productivity Growth

3.3.1 Methodology

As outlined in the introduction, the German productivity demise exists not only in absolute terms as labor productivity has been declining secularly over the past decade, but also in relative terms as productivity has been falling even further behind the industry-leading US. In order to uncover the sources of Germany's aggregate productivity demise, we seek to trace the aggregate origins to differences in US-German industry-level labor productivity. In this section we outline a methodology that "preserves the underlying industry detail yet maintains conclusions consistent with the aggregate results without arbitrary and inappropriate aggregation assumptions" (Jorgenson, Ho, Samuels and Stiroh, 2006, p.1).

To quantify the industry contributions to aggregate productivity, we apply the *aggregation over industries* method developed by Jorgenson, Gallop and Fraumeni (1987).[49] Industry-level gross output growth can be decomposed into input and TFP contributions according to

$$\Delta \ln Y_i = \bar{v}_{K,i}^{IT} \Delta \ln K_i^{IT} + \bar{v}_{K,i}^{NON} \Delta \ln K_i^{NON} + \bar{v}_{L,i} \Delta \ln L_i + \bar{v}_{X,i} \Delta \ln X_i + TFP_i , \qquad (1)$$

where for industry i, Y_i is gross output, K_i^{IT} are ICT capital services, K_i^{NON} are Non-ICT capital services, L_i represents labor services and X_i are intermediate inputs. The $\bar{v}$'s are the two period-average nominal input shares. Labor services are defined as $\Delta \ln L_i = \sum_j \bar{\varpi}_{j,i} \Delta \ln H_{j,i}$, where $H_{j,i}$ are hours worked of labor (skill) type j in industry i and $\bar{\varpi}_{j,i}$ is the two period average compensation share of labor type j in total labor compensation of industry i.

To relate industry gross output to value added we rewrite equation (1) as

$$\Delta \ln Y_i = \bar{v}_{V,i} \Delta \ln V_i + \bar{v}_{X,i} \Delta X_i , \qquad (2)$$

[49] For recent industry studies applying this method, see, for example, Jorgenson, Ho and Stiroh (2005a), Jorgenson, Ho, Samuels and Stiroh (2006) and Inklaar, O'Mahony and Timmer (2005).

where V_i is value added and $\overline{v}_{V,i}$ is the nominal share of value added in gross output of industry *i*. Combining equations (1) and (2), allows us to write industry value added growth as

$$\Delta \ln V_i = \frac{\overline{v}_{K,i}^{IT}}{\overline{v}_{V,i}} \Delta \ln K_i^{IT} + \frac{\overline{v}_{K,i}^{NON}}{\overline{v}_{V,i}} \Delta \ln K_i^{NON} + \frac{\overline{v}_{L,i}}{\overline{v}_{V,i}} \Delta \ln L_i + \frac{1}{\overline{v}_{V,i}} TFP_i . \quad (3)$$

Defining aggregate output as the weighted average of industry value added, $\Delta \ln V \equiv \sum_i \overline{w}_i \Delta \ln V_i$ (where $\overline{w}_i$ is the average share of industry value added in aggregate value added) and combining this expression with equation (3), we obtain

$$\sum_i \overline{w}_i \Delta \ln V_i = \sum_i \left(\overline{w}_i \frac{\overline{v}_{K,i}^{IT}}{\overline{v}_{V,i}} \Delta \ln K_i^{IT} + \overline{w}_i \frac{\overline{v}_{K,i}^{NON}}{\overline{v}_{V,i}} \Delta \ln K_i^{NON} + \overline{w}_i \frac{\overline{v}_{L,i}}{\overline{v}_{V,i}} \Delta \ln L_i + \overline{w}_i \frac{1}{\overline{v}_{V,i}} \Delta \ln TFP_i \right) \quad (4)$$

where $\left(\overline{w}_i \Delta \ln TFP_i\right) / \overline{v}_{V,i}$ represents the "Domar-weighted" industry-level TFP growth with "Domar-weights" being the quotient of the share of industry value added in aggregate value added, and the share of industry value added in industry gross output.

We are specifically interested in the industry contributions to ALP, which is conventionally defined as $\Delta \ln ALP = \Delta \ln V - \Delta \ln H$, where $\Delta \ln V$ is the Tornqvist index of weighted industry value added defined in equation (4) and H is the unweighted sum of industry hours H_i. H_i is in turn the unweighted sum of hours worked over different labor types $H_i = \sum_j H_{j,i}$. Following Stiroh (2002) ALP can then be decomposed as:

$$\Delta \ln ALP = \sum_i \overline{w}_i \Delta \ln ALP_i + \left(\sum_i \overline{w}_i \Delta \ln H_i - \Delta \ln H \right) = \sum_i \overline{w}_i \Delta \ln ALP_i + R^H \quad (5)$$

The first term on the right hand side represents direct industry contributions to ALP growth and R^H reflects the reallocation of hours.[50] Defining $\Delta \ln k_i^{IT}$, $\Delta \ln k_i^{NON}$, and

[50] The contribution of an industry to aggregate reallocation of hours is approximately the growth in total hours worked and the difference between the two-period average industry value-added share and the two-period average employment share. Thus, the contribution is positive if an industry with an ALP level above (below) the aggregate average level experiences positive (negative) growth in hours.

$\Delta \ln q_i$ as ICT capital deepening, Non-ICT capital deepening and labor quality growth, (4) and (5) yield[51]

$$\Delta \ln ALP = \sum_i \overline{w}_i \left(\frac{\overline{v}_{K,i}^{IT}}{\overline{v}_{V,i}} \Delta \ln k_i^{IT} + \frac{\overline{v}_{K,i}^{NON}}{\overline{v}_{V,i}} \Delta \ln k_i^{NON} + \frac{\overline{v}_{L,i}}{\overline{v}_{V,i}} \Delta \ln q_i + \frac{1}{\overline{v}_{V,i}} \Delta \ln TFP_i \right) + R^H \quad (6)$$

The APL decomposition in (6) has the advantage that input contributions or TFP contributions to APL from any industry subset simply equal the (weighted) sum of contributions from all industries in the subset.

3.3.2 Growth Accounting Results

We begin our analysis with the standard decomposition of APL growth into five main contributions from 1) ICT capital deepening, 2) Non-ICT deepening, 3) labor quality growth, 4) TFP growth, and 5) the reallocation of hours. This decomposition follows the "bottom-up" approach outlined in the previous section (equation 6). Table 3.1 displays the results for the three sample periods (1991-1995, 1995-2000, 2000-2003) as well as the differences in contributions between the two break points (1995, 2000).[52]

The first three rows decompose labor productivity growth into value added growth and labor hour growth. The decomposition highlights the strong, negative drag on German growth from the secular decline in hours worked. The main culprits are German unification, systemic high unemployment, reductions in work weeks, and earnings inequality (see Bell and Freeman, 2001). Annual output growth rates for the total economy would have been approximately one percent higher, had working hours not dropped so dramatically. The phenomenon is well known and documented as a key factor that has been driving a wedge between US and German output growth (see e.g. Blanchard 2004).

The following rows of Table 3.1 dissect labor productivity into the contributions from capital deepening, TFP growth, labor quality, and hours reallocation.

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[51] The growth rate of labor quality is defined as :

$$\Delta \ln q_i = \Delta \ln L_i - \Delta \ln H_i = \sum_j \overline{\omega}_{j,i} \Delta \ln H_{j,i} - \Delta \ln H_i$$

[52] To compare our results to the US we choose time periods that coincide best with Stiroh (2006).

Table 3.1: Sources of German Labor Productivity Growth, 1991-2003

	1991-1995	1995-2000	2000-2003	1995-2000 Less 1991-1995	2000-2003 Less 1995-2000
Total Economy Labor Productivity Growth	**2.31**	**2.04**	**1.57**	**-0.27**	**-0.47**
Aggregate Value Added Growth	1.38	2.01	0.43	0.63	-1.58
Aggregate Hours Growth	-0.93	-0.03	-1.14	0.90	-1.11
Contributions **to Labor Productivity:**					
1) Capital Deepening (Total)	**1.02**	**0.88**	**1.14**	**-0.14**	**0.26**
1.1) *of which* ICT capital deepening	*0.23*	*0.33*	*0.29*	*0.10*	*-0.04*
1.1.1)*Generated in ICT-Prod. industries*	0.07	0.05	0.06	-0.02	0.01
1.1.2) *Generated in ICT-Using industries*	0.12	0.21	0.13	0.09	-0.08
1.1.3) *Generated in Non-ICT industries*	0.04	0.07	0.10	0.03	0.03
1.2) *of which* Non-ICT capital deepening	*0.79*	*0.55*	*0.85*	*-0.24*	*0.30*
1.2.1) *Generated in ICT-Prod. industries*	0.10	0.04	0.03	-0.06	-0.01
1.2.1) *Generated in ICT-Using industries*	0.39	0.20	0.27	-0.19	0.07
1.2.3) *Generated in Non-ICT industries*	0.30	0.31	0.55	0.01	0.24
2) Total Factor Productivity Growth (Total)	**0.35**	**0.47**	**-0.01**	**0.12**	**-0.48**
2.1) *Generated in ICT-Prod. industries*	0.07	0.27	0.17	0.20	-0.10
2.2) *Generated in ICT-Using industries*	-0.03	0.37	0.13	0.40	-0.24
2.3) *Generated in Non-ICT industries*	0.31	-0.17	-0.31	-0.48	-0.14
3) Labor Quality Growth	**0.27**	**0.13**	**0.23**	**-0.14**	**0.10**
4) Hours Reallocation	**0.67**	**0.56**	**0.21**	**-0.11**	**-0.35**

Notes: All figures are average annual percentages. The contributions of inputs are growth rates multiplied by average input shares. TFP refers to Domar-weighted TFP. ICT-Producing industries defined according to DeStatis (2006). ICT-Using industries are Non-ICT Producing industries whose ICT capital share exceeded the median in 1995. Data source: Röhn et al. (2007) and authors' calculations.

Capital deepening contributes by far the greatest share to German average labor productivity in all periods, highlighting the crucial role of investment for labor productivity. The decomposition of capital deepening into ICT and Non-ICT capital deepening provides further information. The gap between the ICT and Non-ICT capital contributions narrowed substantially in 1995-2000. ICT capital deepening contributed about 20 percent to total economy capital deepening in each period, except between 1995 and 2000 when its contribution doubled to almost 40 percent. It is interesting to see that ICT-Using industries were the driving force behind the capital dynamics between 1991-1995 and 1995-2000, when ICT-capital deepening surged and Non-ICT capital deepening declined. Jorgenson, Ho and Stiroh (2005a) point out that the substitution from Non-ICT capital to ICT capital was simply a reaction to sharp declines in ICT prices during that period. In Germany, however, the surge in ICT investment could not offset the sharp decline in Non-ICT capital investment leading to an overall decline in capital deepening.

Nevertheless, one might easily conclude that the increases in ICT capital deepening represent evidence of healthy ICT investment levels in Germany that facilitated the structural transformation towards the information economy. Comparisons with US ICT investment reveal, however, a remarkable German deficit. Jorgenson, Ho, Samuels and Stiroh (2006, Table3) report only slightly higher labor productivity growth in the US as compared to Germany during 1995-2000 (2.13 percent compared to Germany's 2.04 percent) and even lower Non-ICT capital deepening contributions (0.41 percent vs. 0.55 in Germany). However, US ICT capital deepening significantly outpaced ICT capital deepening in Germany, being *three times* higher in the US than in Germany.

The increase in German ICT capital deepening was accompanied by a surge in ICT-Intensive industries' TFP growth. Almost one third of all German labor productivity growth from 1995 to 2000 is attributable to efficiency improvements in ICT-Intensive industries. In particular, the contribution from ICT-Producing industries' TFP to labor productivity quadrupled after 1995. This observation is especially striking given the small size of this sector (about 5 percent of aggregate value added) and suggests extraordinary efficiency gains from ICT production in Germany. At the same time, however, TFP contributions from Non-ICT industries collapsed post 1995, resulting in a negative contribution from this set of industries.

Nevertheless, the positive impact of ICT capital deepening and ICT-Intensive industries' TFP contributions prevented a steeper decline in German labor productivity growth than the observed -0.27 percent reduction from 1991-1995 to 1995-2000. At the same time, however, productivity increased in the US. Not only was German ICT capital deepening significantly lower than in the US, but the decline in Non-ICT capital deepening and the collapse in Non-ICT industries' productivity were also accompanied by reductions in the contributions of labor quality and reallocations of hours.

The second labor productivity slowdown post 2000 was driven by different, if not opposing, factors. Table 3.1 shows that German ICT capital deepening and ICT-Producing industries' TFP growth declined by about 25 percent. Most important was, however, the change in productivity growth of Non-ICT-Producing industries. TFP contributions from ICT-Using industries weakened significantly, and the contributions of Non-ICT industries to APL continued to decline even further to -0.31. For the economy as a whole, this led to a dramatic collapse in TFP contributions from 0.47 percent in 1995-2000 to -0.01 percent in 2000-2003.

In the US, the 1995-2000 surge in ICT investment was followed by a surge in the contribution of Non-ICT production TFP to productivity. Van Ark and Inklaar (2005), for example, report contributions of Non-ICT-Production TFP of 1.4 percent (a sharp 1 percentage point acceleration compared to the 1995-2000 level). One possible explanation may be that this represented the diffusion of ICT investment to the rest of the US economy. In sharp contrast, German Non-ICT-Producing industry TFP growth declined so dramatically that it registered a negative contribution to labor productivity post 2000. It was a broad resurgence of Non-ICT capital deepening that mitigated the second German productivity reduction. This resurgence was largely carried by increased contributions from ICT-Using and especially Non-ICT industries.

In summary, a key source of the first productivity decline was insufficient ICT capital deepening relative to the US levels. German ICT capital deepening was insufficient to offset the decline in Non-ICT capital deepening which was associated with a sharp drop in Non-ICT industries' TFP growth. The origin of the second reduction in German labor productivity was the insufficient diffusion of ICT investment to Non-ICT-Producing industries. The dramatic decline in German TFP growth raises serious questions about a departure from the technology frontier. In the next section we take a closer look at the productivity contributions of each of the 52 industries and present head to head industry comparisons with the US.

3.4 The Evolution of ICT Industries in Germany and the US

3.4.1 German Labor Productivity Contributions by Industry

In this section we identify the exact industries that drove Germany's productivity performance. Figure 3.2a-c are modified Harberger (1998) diagrams that display each industry's contribution to cumulative value added on the horizontal axis, while the vertical axis plots the contributions to cumulative total industry labor productivity growth.[53] Industries with positive slopes contribute to labor productivity and those along the negatively sloped part of the curve generated a drag on productivity growth. How important a given industry's contribution (or drag) is depends on the horizontal distance between points.

Figure 3.2a-c highlights the heterogeneity of labor productivity contributions across industries and time. Surprising is the large and increasing numbers of industries that contributed negatively to German labor productivity. For example, from 1991-1995, fourteen industries contributed negatively, but by 2000-2003 over 40 percent of German industries (21 of the 52) reduced the nations overall labor productivity. Even more striking is the large share of total value added comprised by firms that had negative labor productivity growth. Industries that constituted between 40 percent (1991-1995) and 25 percent (1995-2000) to German value added output contributed negatively to productivity growth. Only half (26 of the 52) industries contributed consistently positively to German labor productivity from 1991 to 2003.

Top contributors to total industry labor productivity growth in all periods are the Communications and Wholesale Trade industries, whereas Other Business Services exerted a strong drag on German labor productivity growth throughout.[54] Notable are also the performances of the Office Machinery & Computers industry as well as Financial Intermediation, which made strong contributions in the second period, but declined post 2000. In contrast, Real Estate and Motor Vehicles were among the weakest performers during 1995-2000 but posted strong productivity gains after 2000. In particular, the Real Estate sector made by far the largest contribution during the last period, adding 0.51 percent to APL growth.

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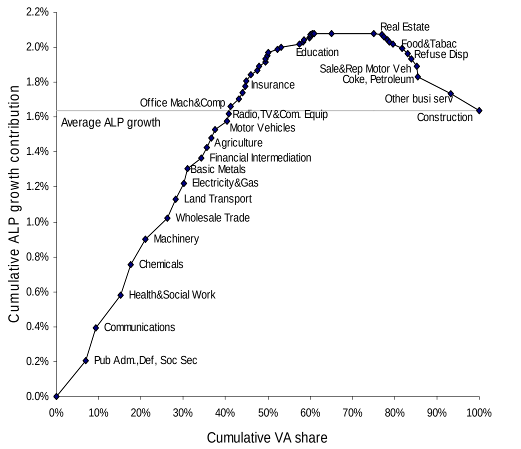
[53] A complete listing of each industry's contribution to aggregate ALP growth is provided in Table 3.A1.

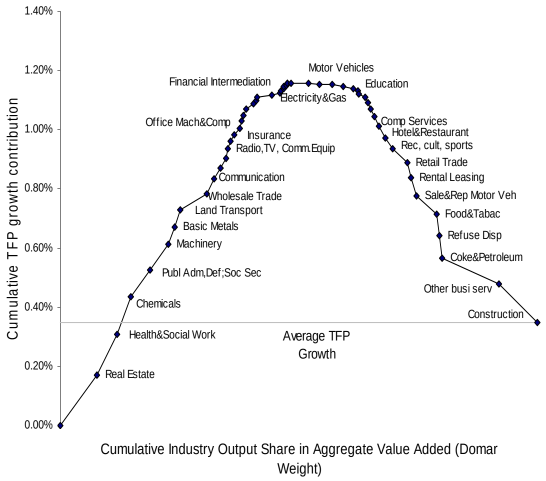
[54] Other Business Services comprise such diverse services as legal, accounting, book keeping and auditing services; tax consultancy; market research and public opinion polling; business and management consultancy; holdings; architectural and engineering activities and related technical consultancy; technical testing and analysis; advertising; labor recruitment and provision of personnel; investigation and security activities, industrial cleaning as well as miscellaneous business activities not otherwise mentioned.

Figure 3.2: Industry ALP and TFP Contributions

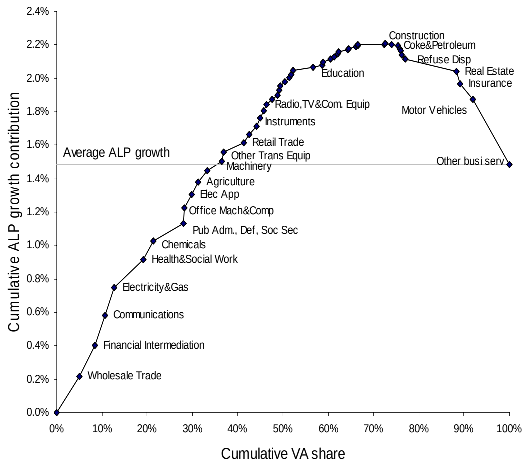
a) ALP, 1991-1995



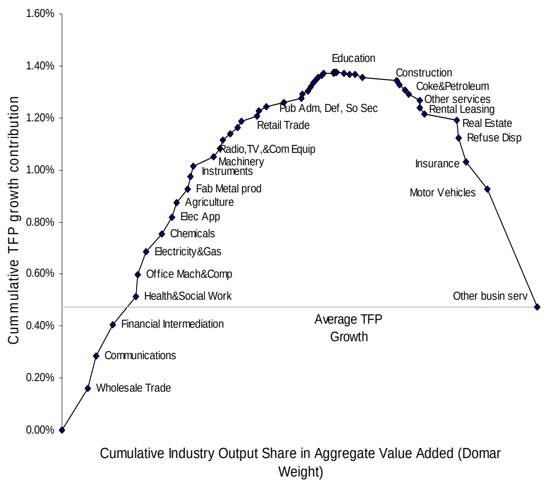
d) TFP, 1991-1995



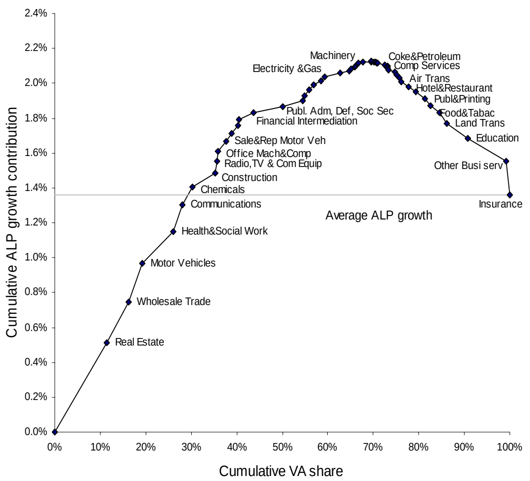
b) ALP, 1995-2000



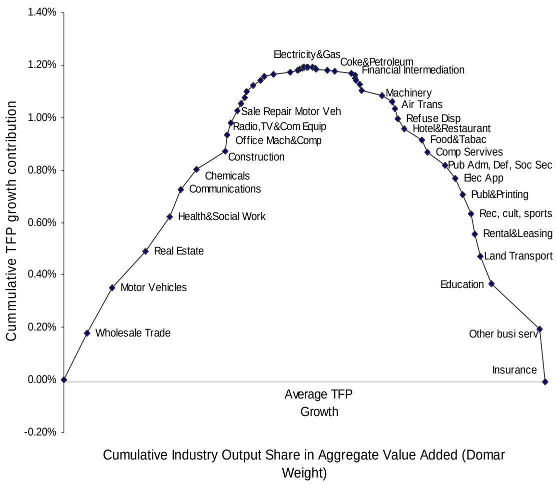
e) TFP, 1995-2000



c) ALP, 2000-2003



f) TFP, 2000-2003



Data source: DeStatis, Röhn et al. (2007), and authors' calculations.

Instead of examining the *within* period contributions of industries, we are, of course, especially interested in uncovering the drivers of the two-stage German productivity demise. Therefore, we examine the *changes* in productivity contributions over time. Table 3.2 identifies those industries that contributed directly to the decline in productivity observed after 1995 and 2000. Only three industries with value added shares greater than one percent saw consecutive increases in their contributions to labor productivity (Construction, Vehicle Sales and Repair, and Wholesale Trade). In contrast, the number of industries with secularly declining contributions to labor productivity is large: thirteen industries with a cumulative share of German value added of over 20 percent are lead by Public Administration, Machinery, and Chemicals.

Just about half of the industries (24 out of 52) contributed negatively to labor productivity during the first slowdown. Even more worrisome, the second slowdown was driven by an even larger number of 35 declining industries. Table 3.2 tallies the performance across periods and shows that the majority of industries, however, (33 out of 52, constituting 67 percent of value added) experienced a reversal of their productivity fortunes between 1991 and 2003. Real Estate, Other Business Services and Motor Vehicles drove much of the slowdown post 1995, but all three industries reversed their performances and contributed strongly to productivity post 2000. Note however, that we know from Figure 3.2c that the absolute productivity contribution from Other Business Services was negative, hence this industry contributed only by reducing its drag on productivity. In contrast, Financial Intermediation and Retail Trade were among the largest positive contributors post 1995, who then had strongly negative contributions to labor productivity post 2000. Real Estate and Other Business Services are classified as Non-ICT-Using industries, whereas Financial Intermediation and Retail Trade are ICT-Using. This helps us pinpoint the industries that are largely responsible for the underlying dynamics of the first and second productivity declines.

Table 3.2: Changes in Industry Contributions to Labor Productivity

	VA (%)	1st Change < 0	2nd Change > 0		VA (%)	1st Change > 0	2nd Change > 0
Real Estate	11.87	-0.07	0.58	Wholesale Trade	4.83	0.10	0.01
Other Business Services	8.73	-0.29	0.26	Construction	4.46	0.10	0.08
Health & Social Work	7.19	-0.02	0.01	Sale/Repair vehicles	1.85	0.05	0.05
Motor Vehicles	3.21	-0.14	0.32	Sewage Refuse Disp.	0.64	0.01	0.01
Auxiliaries Transport	1.51	-0.02	0.01	Coke, Petroleum,	0.28	0.04	0.01
Plastic & Rubber	1.08	-0.01	0.01	Water Transport	0.23	0.01	0.01
Aux. Fin/Insur. Interm.	0.53	0.00	0.01				
Radio, TV, Comm. Equip.	0.52	-0.01	0.03				
Textiles	0.26	-0.01	0.00				
Energy Mining & Quarrying	0.09	-0.06	0.01				
Leather	0.06	-0.01	0.00				
Count	**11**			**Count**	**6**		
Sum	**35.03**	**-0.63**	**1.25**	**Sum**	**12.28**	**0.31**	**0.16**

	VA (%)	1st Change < 0	2nd Change < 0		VA (%)	1st Change > 0	2nd Change < 0
Pub. Adm., Def, Social Sec.	6.21	-0.10	-0.07	Education	4.58	0.00	-0.10
Machinery	3.33	-0.09	-0.04	Retail Trade	4.22	0.05	-0.02
Chemicals	2.27	-0.07	-0.01	Fin. Intermediation	3.34	0.12	-0.15
Communications	2.09	-0.01	-0.02	Fab. Metal Products	1.99	0.05	-0.05
Land Transport	1.54	-0.09	-0.08	Food & Tabacco	1.96	0.03	-0.05
Other services	1.41	-0.03	-0.00	Rec., Cultural, Sports	1.93	0.02	-0.06
Basic Metals	0.89	-0.04	-0.02	Rental & Leas. Serv.	1.82	0.02	-0.05
Organizations, nec	0.86	0.00	-0.01	Electricity, Gas	1.63	0.08	-0.14
Insurance	0.73	-0.11	-0.11	Hotels & Restaurants	1.59	0.02	-0.03
Non-Metallic Min. Prod.	0.72	-0.03	0.00	Computer Services.	1.58	0.04	-0.04
Wood Products	0.36	-0.01	-0.01	Electr. Apparatus nec	1.56	0.04	-0.11
Air Transport	0.28	-0.02	-0.04	Agric., Forestry, Fish.	1.12	0.02	-0.03
Mining/Quarry, ex. Energy	0.12	-0.01	-0.02	Publishing, Printing	1.08	0.04	-0.09
				Instruments	0.90	0.03	-0.04
				Furn. /Misc. Manuf.	0.55	0.03	-0.02
				Paper, Pulp	0.53	0.02	-0.03
				Other Transp. Equip.	0.49	0.07	-0.02
				R&D	0.38	0.01	-0.04
				Water supply	0.29	0.01	-0.00
				Office Mach & Comp.	0.18	0.05	-0.03
				Apparel	0.14	0.00	-0.00
				Recycling	0.05	0.00	-0.00
Count	**13**			**Count**	**22**		
Sum	**20.79**	**-0.62**	**-0.43**	**Sum**	**31.89**	**0.79**	**-1.10**

Notes: VA is the value added share of an industry in 2003. 1st Change is the difference of an industry ALP contribution between 1991-1995 and 1995-2000. 2nd Change is the 1995-2000 and 2000-2003 difference. Source: DeStatis and Röhn et al. (2007).

We can now utilize the data in Stiroh (2006) to highlight the source of the diverging labor productivity experience with head to head US/German industry comparisons.[55] Figure 3.3a, b displays industry contributions to the two labor productivity slowdowns (surges) in Germany (US). It is immediately apparent from Figure 3.3a that most of the US/German differences between the first two periods can be

[55] US and German industry classifications differ, requiring us to merge 51 German and 60 US industries into 37 industries that represent a consistent harmonization. The German Public Administration, Defense and Social Security sector is excluded since US data focuses on the private sector. The periods under consideration differ slightly: Stiroh's first period begins 1988 and his last period ends 2004.

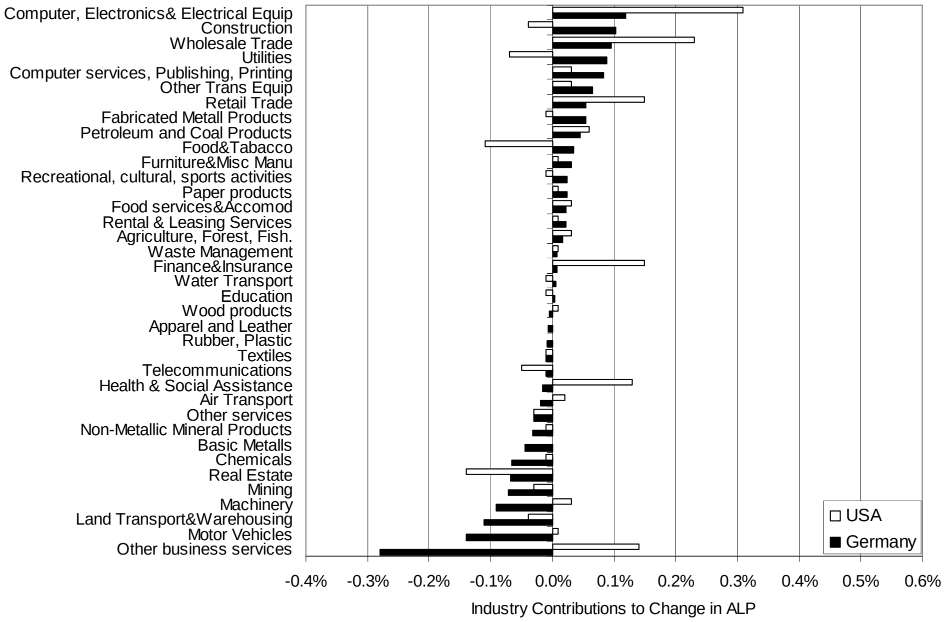
traced to a few ICT-Intensive industries. Computer & Electronics Equipment, Wholesale Trade, and Retail Trade made positive contributions in both countries, but the gains were two to three times greater in the US. Further, Finance & Insurance contributed substantially to the first productivity surge in the US while its contribution in Germany was close to zero. Most striking is the divergence in the Other Business Services, which was a major contributor of the productivity surge in the US while it exerted the largest drag on German productivity growth. It is surprising that key industries which have traditionally been beacons of German productivity – Machinery and Motor Vehicles – also contributed significantly to the productivity slowdown while they added to the productivity surge in the US.

Turning to the industry origins of the diverging productivity trends post 2000 in Figure 3.3b, we make two important observations. First, a completely different set of industries explains the widening productivity gap. For example, we find the largest differences in US/German productivity arise in Computer Services, Telecommunication, Utilities, and Food & Tobacco. Note that all of these industries had actually mitigated the productivity divergence in US and German productivity post 1995. Second, a larger number of German industries is responsible for the prolonged divergence in US versus German productivity. During the first productivity divergence post 1995, 22 industries contributed to the divergence while this number increased to 27 industries post 2000. This constitutes a worrisome implication: the post 2000 productivity (decline) surge in the US (Germany) is driven by larger group of industries than the first divergence in the late 1990s.

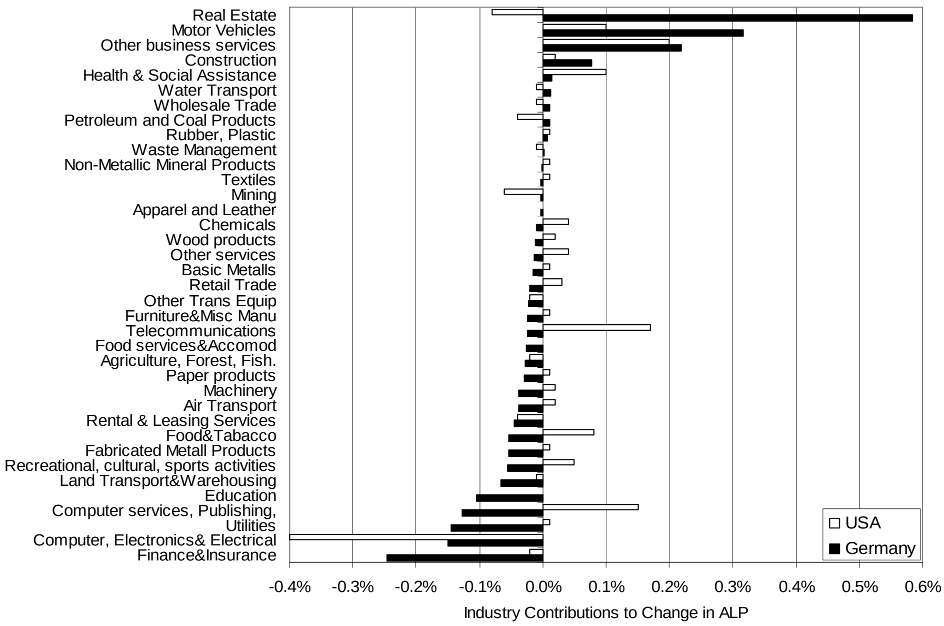
Our US-German comparisons share similarities with the US-EU comparisons of van Ark and Inklaar (2005). In their study, similar industries contributed to the US-EU divergence (especially Trade and Finance) post 1995, which may indicate that the US pulled away from all of Europe, and not only from Germany. Novel are our results that the origins of this divergence changed dramatically post 2000.

Figure 3.3: Industry Contributions to Change in Labor Productivity

a) Post 1995



b) Post 2000



Source: Stiroh (2006), DeStatis, Röhn et al. (2007), and authors' calculations.

3.4.2 German TFP Contributions by Industry

Figure 3.2d-f plots the modified Harberger (1998) diagram for the individual industry TFP growth contributions for the three periods 1991-1995, 1995-2000 and 2000-2003. The vertical axis displays the cumulative industry contributions to aggregate TFP growth, while the horizontal axis plots the cumulative industry output share in total value added (Domar-weights). The heterogeneity of TFP growth contributions among industries is striking. The curves are surprisingly steep indicating a bifurcated economy with either strong productivity gains or sharp productivity losses. Most importantly, the share of industries that contribute negatively over time is increasing dramatically. This is especially apparent if we compare the 1995-2000 and 2000-2003 periods in Figure 3.2e, f. In 1995-2000, 17 industries experienced negative TFP growth rates, featuring large contractions in Other Business Services, Motor Vehicles and the Insurance industry. In 2000-2003, in contrast, 28 industries accounting for almost 50 percent of aggregate value added showed negative TFP growth.

Comparing the first two periods in Figure 3.2d, e, it is striking that Wholesale Trade and Financial Intermediation (both ICT-Using) increased their TFP contributions substantially between the two periods. The same is true for Office Machinery & Computers and Communications (both ICT-Producing). Of these industries only Wholesale Trade managed to increase its TFP growth contribution further post 2000 when TFP growth in Communication and Office Machinery & Computer slowed, and Financial Intermediation TFP turned negative. Contributions from the Insurance, Machinery and the Government sector steadily declined over the three periods, pointing to severe problems within these industries. These industries started with positive TFP growth but showed negative TFP growth post 2000.[56]

3.5 ICT and Productivity

So far we have focused on the industry productivity *contributions* to aggregate labor productivity. In this section, we investigate formally whether industries that invested heavily in ICT can be shown to exhibit significantly higher productivity *growth rates*. Table 3.1 seems to imply a strong relationship between the two, at least

[56] A summary of each industry's TFP contribution is provided in Table 3.A1.

for the period 1995-2000, when ICT-Intensive industries saw strong TFP increases at the time during which they also experienced a surge in ICT capital deepening. To identify the link between ICT intensity and productivity, we follow the methodology of Stiroh (2006) and apply a difference-in-difference estimator to compare industry productivity pre and post our 1995 and 2000 break years.

$$\Delta \ln prod_{i,t} = \alpha + \beta * Post_T + \gamma * ICT_T + \delta * Post_T * ICT_T + \varepsilon_{i,t}, \qquad (7)$$

where the change in the log of labor productivity in industry i at time t is given by $\Delta \ln prod_{i,t}$ and $Post_T$ is a dummy identifying observations after a given break year T. ICT_T is a dummy for ICT-Intensive industries at time T. Our measure of productivity is labor productivity measured as value added per hour worked.[57]

The interpretation of the coefficients in equation (7) is that β represents the acceleration in ALP growth for our control group (Non-ICT industries) after a break year. Relative ALP growth rates of ICT-Intensive industries prior to the break year are given by γ, and δ indicates the ALP acceleration of ICT-Intensive relative to Non-ICT-Intensive industries after the break year. We estimate (7) using OLS, where we allow the error term $\varepsilon_{i,t}$ to be correlated within industries over time (see Stiroh, 2006). Table 3.3 reports the estimation results with value added labor productivity growth as the dependent variable. The first column includes only the post 1995 dummy and shows that on average all industries saw a 0.4 percent deceleration of labor productivity growth post 1995. It is not surprising that the coefficient is not significant since we have not accounted for the opposite experiences of ICT and Non-ICT Industries documented extensively above.

The second column displays results for the complete specification in equation (7). Post 1995 Non-ICT Industries saw a statistically significant 2 percent deceleration of their labor productivity growth, while ICT-Intensive industries experienced a statistically significant 3.1 percent higher acceleration. This result is consistent with our summary statistics above, where we find that the first productivity slowdown is caused by a deceleration of productivity in Non-ICT Industries that was mitigated by

[57] Industry TFP as the dependent variable generates qualitatively similar results. We drop an extreme outlier in all specifications: the Petroleum and Coke industry, which constitutes 0.3 percent of German value added. It reports labor productivity swings of over 100 percent.

Table 3.3: Labor Productivity Accelerations 1991-2003

	Dependent variable: Average Labor Productivity Growth (value added)					
Dummy_Post1995	-0.39 (0.84)	-1.97** (0.89)	-1.97** (0.89)			
Dummy_ICT1995		-0.83 (1.15)	-1.60 (1.10)			
Post1995*ICT1995		3.09* (1.62)	1.89 (1.52)			
Dummy_Post2000				-1.99*** (0.74)	-2.26** (0.94)	-2.26** (0.94)
Dummy_ICT2000					0.79 (1.36)	-0.63 (1.02)
Post2000*ICT2000					0.53 (1.47)	-0.22 (1.59)
Drop ICT-Producing Industries			yes			yes
No. Obs	612	612	552	612	612	552
No. Industries	51	51	46	51	51	46
R^2	0.00	0.01	0.01	0.01	0.01	0.01

Notes: Robust standard errors that allow for correlation within industries over time in parentheses. ***, **, * indicate 1 percent, 5 percent, 10 percent significance levels. Source: Röhn et al. (2007) and authors' calculations.

ICT-Intensive industries. Going one step further, we drop ICT-Producing industries from the sample and examine only ICT-Using and Non-ICT-Using industries. In this case the positive impact of ICT is smaller (1.9 percent) and statistically insignificant. These findings are also consistent with our above results where most of the ICT-productivity contributions resulted in ICT-Producing industries.

The last three columns replicate the same analysis for the second productivity slowdown. The break year is now set to 2000 and industries are classified as ICT-Intensive based on their ICT-capital share in 2000. Now the picture changes as Non-ICT-Intensive industries again saw a significant labor productivity deceleration (2.3 percent). However, ICT-Intensive industries did not experience significantly higher productivity growth. Moreover, if we drop ICT-Producing industries from the sample, labor productivity growth for ICT-Using industries decelerated even faster (0.2 percent) – albeit not significantly – than in Non-ICT-Industries. This confirms our earlier finding that ICT-Using industries were a drag on German productivity growth due to their TFP growth declines post 2000.

In sum, we find strong evidence that ICT-Intensive industries had significantly higher labor productivity growth than the Non-ICT Industries post 1995.

These gains originated, however, largely in the small category of ICT-Producing industries. The productivity advantage of ICT-Intensive industries was, however, only transitory. For the post 2000 period, ICT-Intensive industries did not experience higher productivity growth compared to Non-ICT industries. If anything, our results suggest that productivity growth in ICT-Using industries decelerated even stronger than in Non-ICT industries post 2000.

3.6 Summary and Conclusions

Labor productivity has experienced two surges in the United States, one around 1995 and the other post 2000. In contrast, Germany experienced two successive productivity reductions in the same time periods. We employ industry-level data from the *ifo industry growth accounting database* (Röhn et al., 2007) to analyze the sources of Germany's productivity demise. We compare our results to the US performance to identify the drivers of Germany's departure from the technology frontier.

The disaggregation to the 52 industry-level allows us to identify clear but distinct sources of the two German productivity declines. The post 1995 slowdown was characterized by a surge in productivity gains in the ICT-Intensive industries, especially in the ICT-Producing industries. The origin of this productivity surge was the substitution of investment from Non-ICT-capital to ICT-capital. Compared to the US, however, German productivity gains in these ICT-Intensive industries were small (particularly Trade, Finance and ICT-manufacturing). Our estimates identify that the source of the weak productivity gains rests in the lackluster performance of German ICT-Using industries. Ultimately the productivity gains in ICT-Intensive industries were too small to offset large productivity reductions in Non-ICT industries.

The sources of the second productivity slowdown were different. The positive impact of ICT-Intensive industries vanished after 2000, as these industries' ICT capital deepening and TFP growth decelerated significantly. Non-ICT productivity never recovered, however. We can only surmise that ICT diffusion was significantly smaller in Germany than in the US. The resurgence of Non-ICT capital deepening was too small to prevent a second aggregate productivity decline.

Comparing the sources of the second productivity decline in Germany post 2000 to the first post 1995, we make two especially worrisome observations. First, the number of industries experiencing negative TFP growth increased dramatically after 2000. 28 out of 52 industries accounting for almost 50 percent of aggregate value added showed negative total factor productivity growth. Second, a larger number of German industries was responsible for the prolonged divergence in US versus German productivity. During the first productivity divergence post 1995, 22 industries contributed to the divergence while this number increased to 27 industries post 2000.

Appendix Chapter 3

Table 3.A1: Value-Added Share and ALP, TFP Contributions by Industry

Industry	VA share 2003	ALP Contributions			TFP Contributions		
		1991-1995	1995-2000	2000-2003	1991-1995	1995-2000	2000-2003
Communications [a)]	2.1	0.19	0.18	0.15	0.05	0.13	0.11
Computer & Related Services [a)]	1.6	-0.01	0.03	-0.01	-0.03	0.00	-0.05
Instruments [a)]	0.9	0.01	0.05	0.01	0.00	0.04	0.00
Radio, TV & Comm. Equipment [a)]	0.5	0.05	0.04	0.07	0.03	0.03	0.05
Office Machinery & Computers [a)]	0.2	0.04	0.09	0.06	0.02	0.09	0.06
Health, Social Work [b)]	7.2	0.18	0.17	0.18	0.14	0.11	0.13
Wholesale Trade [b)]	4.8	0.12	0.22	0.23	0.05	0.16	0.18
Construction [b)]	4.3	-0.10	0.00	0.08	-0.13	-0.01	0.07
Retail Trade [b)]	4.2	0.00	0.05	0.03	-0.05	0.02	0.01
Financial Intermediation [b)]	3.5	0.06	0.18	0.04	0.01	0.12	-0.01
Machinery [b)]	3.3	0.15	0.06	0.02	0.08	0.04	-0.02
Motor Vehicles [d)]	3.3	0.05	-0.09	0.23	0.00	-0.10	0.18
Sale, Repair Motor vehicles [b)]	1.8	-0.04	0.01	0.06	-0.06	0.00	0.05
Rental. Leasing Services [b)]	1.9	0.03	0.05	0.00	-0.05	-0.03	-0.08
Rec., Cultural, & Sports Activities [b)]	1.9	-0.01	0.02	-0.04	-0.04	0.00	-0.07
Electrical Apparatus n.e.c. [b)]	1.6	0.04	0.08	-0.03	0.00	0.06	-0.05
Other Services [b)]	1.4	0.02	-0.01	-0.01	0.00	-0.02	-0.02
Rubber, Plastic [b)]	1.1	0.03	0.02	0.03	0.02	0.02	0.02
Publishing, Printing [b)]	1.0	0.01	0.05	-0.04	-0.01	0.03	-0.06
Organizations, n.e.c[b)]	0.9	0.01	0.01	0.01	0.01	0.01	0.00
Insurance [b)]	0.8	0.04	-0.08	-0.19	0.02	-0.09	-0.20
Other Transport Equipment [b)]	0.5	-0.01	0.05	0.03	-0.02	0.05	0.02
Aux. Fin. & Ins. Intermediation [b)]	0.5	-0.01	-0.02	0.00	-0.02	-0.02	0.00
Research & Development [b)]	0.4	0.01	0.02	-0.02	0.01	0.02	-0.02
Water Transport [b)]	0.2	0.02	0.03	0.04	0.01	0.02	0.02
Recycling [b)]	0.0	0.00	0.00	0.00	0.00	0.00	0.00
Real Estate [c)]	11.7	0.00	-0.07	0.51	0.17	-0.03	0.14
Other Business Services [e)]	8.8	-0.10	-0.39	-0.13	-0.09	-0.45	-0.17
Pub. Admin., Defense, Soc. Security [c)]	6.2	0.20	0.11	0.03	0.09	0.02	-0.05
Education [c)]	4.6	0.01	0.02	-0.09	-0.01	0.00	-0.11
Chemicals [c)]	2.3	0.18	0.11	0.10	0.13	0.07	0.08
Fabricated Metal Products [c)]	2.0	0.02	0.07	0.01	-0.01	0.05	0.00
Food, Tobacco [c)]	2.0	-0.02	0.01	-0.04	-0.06	0.02	-0.04
Electricity, Gas [c)]	1.7	0.09	0.17	0.03	0.01	0.09	0.01
Hotels, Restaurants [c)]	1.6	-0.03	-0.01	-0.03	-0.04	-0.01	-0.04
Land Transport [c)]	1.5	0.11	0.02	-0.06	0.06	-0.02	-0.08
Auxiliary Transport Activities [c)]	1.5	0.05	0.03	0.04	0.03	0.02	0.01
Agriculture, Forestry, Fishing [c)]	1.1	0.06	0.07	0.05	0.02	0.05	0.03
Basic Metals [c)]	0.9	0.09	0.04	0.03	0.06	0.04	0.02
Non-Metallic Mineral Products [c)]	0.7	0.06	0.02	0.02	0.04	0.01	0.01
Sewage & Refuse Disposal [c)]	0.6	-0.03	-0.03	-0.02	-0.07	-0.07	-0.04
Furniture & Misc. Manufacturing [c)]	0.5	-0.01	0.02	-0.01	-0.03	0.01	-0.02
Paper, Pulp [c)]	0.5	0.00	0.03	0.00	-0.01	0.02	-0.01
Wood Products [c)]	0.4	0.02	0.02	0.01	0.02	0.01	0.00
Textiles [c)]	0.3	0.02	0.01	0.01	0.01	0.01	0.00
Coke, Petroleum, Nuclear Fuels [c)]	0.3	-0.06	-0.02	-0.01	-0.07	-0.02	0.00
Water Supply [c)]	0.3	0.01	0.01	0.01	-0.01	0.00	0.00
Air Transport [c)]	0.3	0.04	0.02	-0.02	0.03	0.01	-0.03
Energy Mining & Quarrying [c)]	0.1	0.04	-0.02	-0.01	0.02	-0.02	-0.01
Mining & Quarrying, exc. Energy [c)]	0.1	0.02	0.00	-0.01	0.01	0.00	-0.01
Apparel [c)]	0.1	0.01	0.01	0.01	0.01	0.01	0.01
Leather [c)]	0.0	0.01	0.00	0.00	0.00	0.00	0.00

a) ICT-Producing Industry, b) ICT-Using Industry 1995 and 2000, c) Non-ICT-Intensive Industry d) ICT-Using Industry in 1995, e) ICT-Using Industry in 2000. Notes: Average annual percentages. ALP contributions are labor productivity growth rates multiplied by average value added shares. Contributions of TFP are industry TFP growth rates multiplied by industry output share in aggregate value added (Domar-weight). ICT-Using are Non-ICT-Producing industries whose ICT capital share exceeds the median. ICT-Producing industries are defined according to DeStatis (2006).
Data source: Röhn et al. (2007) and authors calculations.

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