THE LONDON SCHOOL OF ECONOMICS AND POLITICAL SCIENCE

E·S·R·C ECONOMIC & SOCIAL RESEARCH COUNCIL

Trend Growth Durations & Shifts

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SRC Discussion Paper No 71

July 2017

Systemic Risk Centre

Discussion Paper Series

ISSN 2054-538X

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Keywords: Economic Growth, Duration Analysis, Trend Shifts, Trend Extraction

This paper is published as part of the Systemic Risk Centre's Discussion Paper Series. The support of the Economic and Social Research Council (ESRC) in funding the SRC is gratefully acknowledged [grant number ES/K002309/1].

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Published by
Systemic Risk Centre
The London School of Economics and Political Science
Houghton Street
London WC2A 2AE

TREND GROWTH DURATIONS & SHIFTS

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1. Introduction

> "The instability of growth rates makes talk of *the* growth rate almost meaningless."
>
> Lant Pritchett [33]

Many developed and developing countries have been growing at a slower pace since at least the late 2000s. Which ones will continue at a low trend growth rate for another several years? Where could the situation get even worse before it gets any better, and where is a rebound in trend growth imminent?

Such questions are of great interest to many policymakers and investors. However, addressing them in practice is rather challenging for two main reasons. Trend growth is inherently unobserved, with no consensus among economists on how it should be extracted from growth time series data, and a large number of domestic and external

Date: First version: September 2016. This version: April 2017.
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I am very grateful to Anders E. B. Nielsen for guidance and feedback. I also thank Philippe Aghion and participants of the Rimini Conference in Economics and Finance 2016 and the Systemic Risk Centre research meetings for interesting and helpful discussions, comments, and suggestions. This work is part of my Ph.D. research, kindly funded by the Economic and Social Research Council.

factors come into interplay at the very same time, and could either shift the current trend growth rate up, or down, or counterbalance each other and make the country vibrate around the existing trend for another several years.

This paper aims to develop an empirical framework which allows us to address the following two questions: *What is the trend growth rate at which a country is currently growing? How likely is it to shift and in what direction?*

Although numerous sophisticated ways of extracting the trend component from growth time series by applying linear, nonlinear, univariate, multivariate filters and other techniques exist (cf., e.g., French [20]), very often, we still want to think about trend growth as merely a medium/long term average growth rate. Despite its simplicity, this latter definition leads to an important practical issue: given a time series of growth rates over *what* periods of time should the averages be taken?

This issue is rarely addressed explicitly, and averages are often taken over subjectively defined periods of time, decades, the whole sample of data that one has access to, etc., thereby ignoring the large empirical growth literature that started in the 1990s with the seminal contributions of Easterly et al. [15] and Pritchett [33], and which shows that employing "arbitrarily chosen long-run average growth rates fails to take account of a very important 'stylised fact' of economic growth, i.e., while the growth process of "developed" economies is well characterized by such a single long run average growth rate (with a "business cycle" around this trend) this is not true of most countries in the world, many of whom exhibit multiple structural breaks in growth rates" (Kar, Pritchett, Raihan, and Sen [29], henceforth KPRS).

Our paper builds on the insights and techniques of this empirical growth literature to first propose a methodology for extracting the trend as a sequence of medium/long term average growth rates taken such that a shift in trend growth, whenever it happens, satisfies economic significance thresholds, and the trend shift dates identified are optimally located in a growth time series. This method, called the "iterative Fit and Filter" (iFF), generalizes the "Fit and Filter" (FF) approach developed in KPRS [29] to identify breaks in growth time series. iFF preserves the merits of the original FF, in particular, the ability to identify a much larger number of breaks in the presence of high growth volatility than purely statistical methods (Bai-Perron [9, 8]), but overcomes the problem of having to postulate a somewhat arbitrary maximum number of breaks in the first step and the fact that, unlike in purely statistical methods, the final break dates identified by the original FF are not necessarily optimally located. A simple example illustrates how both issues matter for whether or not a potential shift date is identified as true.

iFF is therefore a general method which only requires the researcher to specify two parameters: a minimum number of years over which the averages have to be taken (minimum trend growth duration) and the economic significance threshold(s) for the trend growth shifts (trend shifts significance filter). Both parameters should depend on how the researcher defines trend growth for the purpose of his analysis and the type of trend growth dynamics he is interested in understanding and predicting. In this paper, we are interested in medium/long term trend growth and therefore impose a minimum trend growth duration of five years. We also employ the economic significance thresholds proposed in the original FF which have the advantage of recognizing the non-linearity in the growth process by distinguishing between a trend shift in the same direction (e.g. up-shift after up-shift), in which case a 1% point change is enough for significance, and a shift in the opposite direction (e.g. down-shift after up-shift) where the trend has to change by at least 3% points for a significant shift.

Applying iFF with these parameters on a sample of 153 developed and developing countries, we find that it separates important country-specific historical episodes, and that *trend growth durations* - number of years between two consecutive *trend growth shifts* - vary substantially both across countries and for a given country over time. We discuss in some details the experiences of several countries both to illustrate what iFF identifies in practice and to suggest how it could potentially be employed in economic history research where arbitrarily taken averages are still very often the norm.

Despite the heterogeneity of country experiences, several characteristics seem to clearly distinguish the overall trend growth process in developing countries from the one followed by developed economies. For instance, we find that although growth is twice as volatile in developing countries as in developed ones, trend growth is almost three times as volatile and therefore accounts for a larger proportion of the overall growth variance. The probability that we will have to wait for 10 years or more between two consecutive trend growth shifts in a developing country is only 31% versus 72% for a developed economy. Moreover, the median absolute magnitude of a trend growth shift in a developing economy is 5.45% points versus 2.3% points in a developed counterpart. These findings agree with previous research (e.g. Pritchett [33], Aguiar and Gopinath [4]) that documents and investigates the distinction between the smooth and stable growth paths of developed economies and the discontinuous growth patterns in developing countries.

To address our second motivating question - *"How likely is trend growth to shift and in what direction?"* - we model and estimate the conditional probabilities of trend growth up and down-shifts next year, conditional on the country having already grown at the current trend growth rate since the last trend shift. In competing risks models (an extended form of duration/survival analysis with several possible types of events instead of one), these latter objects are known as cause-specific *discrete-time hazard rates* (cf., for instance, Allison [6]).

Several empirical growth papers have already employed duration techniques. For instance, Mora and Siotis [32] estimate a discrete-time duration model to analyse how external factors affect recovery prospects in developing economies. Berg et al. [12] and Hausmann et al. [24] employ continuous-time duration analysis to investigate the determinants of the duration of growth spells and growth stagnations respectively. The main advantage of the duration methodology is that it allows researchers to incorporate unfinished/censored episodes into their analysis. In our case, this issue is crucial because all current trend growth episodes are censored. The only thing we know about them is that they have already lasted up until this year. What we do not know and are interested in, is whether the country will continue growing at the current trend growth rate for another several years or experience a trend growth shift next year and in what direction. Duration techniques overcome this problem by focusing on the hazard rate, which, in reality, is just a different representation of the distribution of durations but is unaffected by random censoring (cf. for instance Allignol et al. [5]). The random censoring assumption is satisfied if the fact that the growth episode is censored does not provide additional information for whether the country is more or less likely to experience a trend shift next year, which is the case in our setting since our sample ends in 2015 for all countries.

Historically, duration analysis, especially for competing risks, was first mainly developed in a continuous-time setting (Allison [6]). However, already in his seminal paper, where Cox [13] introduced the partial likelihood method for the estimation of the proportional hazards model, he noted that a continuous-time approach may become problematic if the data contains an "appreciable number of ties" - events recorded as happening at the same time. It is, of course, possible to assume that time is continuous and events are simply "grouped" into discrete time intervals and use approximations in the estimation. In our case, however, we believe that considering time as intrinsically discrete, i.e. "ties [as] real, not spurious" (Grambsch and Therneau [21]), is more appropriate since we are directly working with annual data and a large number of countries experience trend shifts simultaneously.

Moreover, a discrete-time approach has the advantage of giving results that are easier to interpret economically. In discrete time, the hazards are conditional probabilities, whereas in continuous time, they are rates and can therefore be bigger than one. For instance, in our case, working in discrete time leads to modelling the conditional probabilities of trend growth shifting up/down next year, conditional on the current trend growth episode having lasted up to this year. If we were to employ a continuous-time approach, we would be estimating the conditional rates at which trend growth episodes end with up/down-shifts per survival year, something that seems to be less intuitive.

Examining a large set of covariates related to the growth environment, the level of development, demographics, institutions, political stability, economic management, and external shocks, we find, for instance, that while better institutions and higher domestic savings may protect countries from trend down-shifts, higher youth and old dependency ratios are detrimental to trend growth, increasing down-shift risks and hindering up-shifts. Several systemic forces, such as higher average gold and rising food prices (except for food exporters), as well as higher and rising US T-bill rates increase the relative trend growth down-shift risks across the globe. A rise in domestic conflict, credit and inflation may act as catalysts for trend growth down-shifts, whereas devaluations, if not too large, may give a positive impetus to trend growth.

As Pritchett and Summers [33], we also find that "regression to the mean is the empirically most salient feature of economic growth". Whatever the specification, a one percentage point higher trend rate increases the relative down-shift risk and reduces the relative up-shift risk by over 20%, while, on its own, the trend growth rate explains almost 10% of all trend shifts.

We then use the insights from our exploratory analysis to construct a parsimonious model which relates the up and down-shift hazards to 20 different covariates, and estimate the 2016 conditional probabilities of up and down-shifts in trend growth for 120 countries in our sample. These hazards estimates, together with the 2015 estimates of trend growth extracted using iFF for all 153 countries, are contained in Table 7 (cf. Appendix), which constitutes the main output of this paper.

For instance, we find that China has been growing at 6.81% p.a. since 2008 (last trend shift in 2007). 2007 was a trend down-shift, hence a further down-shift would be identified as a $\leq 5.81\%$ p.a. average growth rate over the next ≥ 5 years, whereas an up-shift would be a $\geq 9.81\%$ p.a. average growth rate over the same period. In 2016, the conditional probabilities of trend down and up-shifts are 17.3% and 1% respectively.

The rest of the paper is structured as follows. Section 2 presents the trend extraction methodology (iFF) and examples of what it identifies in practice. In Section 3, we establish some stylized facts about trend growth durations and shifts in developing versus developed countries. Section 4 builds our predictive model by first explaining the econometric framework, then undertaking an exploratory analysis of the potential determinants of trend growth durations and shifts.

2. Extracting Trend Growth

Trend growth is unobserved. The assumptions that we impose in order to extract the trend component from growth time series should reflect the way in which we think about the growth process and therefore define what trend growth is. For instance, the well-known Hodrick-Prescott filter [26] extracts trend growth by taking a weighted moving average of the growth time series and therefore assumes that trend growth evolves continuously over time. In this paper, we embrace the basic definition of trend growth as a medium/long term average growth rate and therefore think about the trend as evolving discretely. This section develops a simple iterative algorithm that builds on the "Fit and Filter" (FF) approach proposed in KPRS [29] and extracts trend growth by first identifying economically significant trend shift dates. We start with a precise definition of trend growth in our context, then motivate and describe the trend extraction method, and finally discuss several examples of what it gives in practice.

2.1. **Defining trend growth.** We conceptualize economic growth $\{g(t)\}_{t\in\mathbb{Z}}$ as a process that vibrates around a medium/long term average growth rate - the trend $\{\tau(t)\}_{t\in\mathbb{Z}}$:

$$g(t) = \tau(t) + c(t) \tag{2.1}$$

where the cycle $c(t)$ is a zero-mean transitory fluctuation.

At time t, the trend can shift up:

$$\Delta\tau(t) \equiv \tau(t+1) - \tau(t) > 0$$

or down:

$$\Delta\tau(t) < 0$$

making growth vibrate around a new higher or lower level. Note that $\Delta\tau(t)$ is a forward difference; the trend shift happens in t, but the country starts growing at the new trend growth rate only from period $t+1$.

Suppose that the country is observed for T periods of time over which it experiences $m \geq 0$ trend shifts. As a convention, we set $T_0 = 0$ and $T_{m+1} = T$.[1]

Let $\mathscr{T} = \{T_1, ..., T_m\}$ be the set of shift dates. We want to extract trend growth as a sequence of medium/long term averages:

[1]GDP per capita is observed in $[0, T]$, so growth rates can be computed for periods 1 to T.

$$\tau(t) = \frac{1}{D_j} \sum_{s=T_{j-1}+1}^{T_j} g(s) \text{ for } t \in T_{j-1}+1, ..., T_j,\ j = 1, ..., m+1 \tag{2.2}$$

where $D_j = T_j - T_{j-1}$ is the jth *trend growth duration* - number of years for which the country grows at the trend growth rate at which it started growing in period $T_{j-1} + 1$.

To agree with our basic definition of trend growth as a medium/long term average growth rate that captures some fundamental developments in a country's growth process which go beyond business cycle fluctuations, we want to ensure that:

(1) The averages are taken over a *medium/long term*, i.e for all $j = 1, ..., m+1$:

$$D_j \geq \delta$$

where δ is the minimum trend growth duration - the least number of periods over which the average has to be taken.

(2) Trend shifts are *economically significant,* i.e. for any $t \in \mathscr{T}$:

$$|\Delta\tau(t)| \geq F$$

where F is a threshold that we impose. Intuitively, trend shifts have to be large enough, since they should signal some new fundamental developments in the country's growth process.

The choice of both the minimum trend growth duration δ and the threshold(s) F should depend on the type of trend growth movements that we are interested in.

In this paper, we work with annual growth data and think about trend growth as a medium/long term average growth rate, therefore setting $\delta = 5$. If our interest were only in long term growth, we could set, $\delta = 10$ therefore taking averages over at least decade long intervals.

Similarly, if we believe that an at least 2 percentage points change in a medium/long term average growth rate is economically significant, we can set $F = 2$. If our sole interest were in dramatic trend shifts, we could raise F to 5.

The thresholds could also be non-linear. In this paper, we employ the filter proposed in KPRS [29], which sets $F = 2$ for a first shift, then distinguishes between a trend shift in the same direction (e.g. up-shift after up-shift) with $F = 1$, and a trend shift in the opposite direction (e.g. down-shift after up-shift) with $F = 3$. The idea is that once the trend has already shifted up (down), shifting further up (down) by even 1 percentage point is already economically significant. At the same time, in order to avoid confusing trend shifts and business cycles, the medium/long term average would have to change by at least 3 percentage points if shifting in the opposite direction.

There is no single best answer and, as discussed below, no consensus in the academic literature on what the "right" parameters should be. The framework in this paper is therefore designed specifically to be very flexible and general.

In any case, once we have decided on δ and F, all we need to extract trend growth according to eq.2.3 is to identify the trend shift dates $\mathscr{T}$.

2.2. Identifying trend shift dates.

2.2.1. *The statistical and filter approaches.* Although the ultimate purpose is usually different from extracting trend growth per se, the timing of shifts/breaks in growth time series has been an important preoccupation in many papers. In order to investigate the factors that initiate and halt growth accelerations (Hausmann et al. [23], Berg et al. [12]), growth collapses (Hausmann et al. [24]) or both (Jones and Olken [28], Kerekes [30]), researchers always start by proposing a way of identifying in historical growth data the episodes that are relevant to their study. Since these episodes start with a significant and sustained acceleration/collapse in the average growth rate, their identification relies of the timing of the dates at which such shifts happen.

This empirical growth literature can be broadly classified into two main streams: the papers that use the statistical approach based on the Bai-Perron (BP) methodology [8, 9], and those that employ "filters" - subjectively defined rules that vary from paper to paper.

Given a time series of annual growth rates, the statistical approach (sometimes called the BP methodology) first identifies the sets of break dates that produce the best fit for a given number of breaks, from one up to a maximum. The researcher can impose this maximum number directly and/or specify a minimum number of years between consecutive breaks (akin to the minimum trend growth duration in our case) so that the maximum number of breaks gets determined indirectly by the length of the time series. As mentioned above, there is no consensus on what these numbers should be - Jones & Olken [28] assume a minimum of 5 years between breaks, Berg et al. [12] report results for both 5 and 8, Kerekes [30] opts for 10. In any case, the statistical method then proceeds sequentially: starting from the null hypothesis of no breaks in the time series, it tests whether allowing for additional break(s) significantly improves the goodness of fit.[2] Again, there is no complete agreement on which statistical tests should be employed to gauge this significance - for instance, all previous references [28, 30, 12] employ different tests. This sequential testing continues until we can no longer reject

[2]The standard practice is to allow for one additional break only. However, sometimes the alternative hypothesis is "one or more" as in Berg et al.[12], i.e. a "double maximum" test, cf. discussion in Kerekes [30].

the hypothesis of $m \geq 0$ breaks against the alternative of (one) more break(s) or until reaching the maximum number of breaks allowed/possible.

Whatever the testing procedure, the fundamental problem with the purely statistical approach is that it sometimes identifies *economically* insignificant changes in long term growth averages as *statistically* significant ("false positives"), while omitting some economically significant changes because of statistical insignificance ("true negatives"). For instance, a 2 percentage points change in the medium/long term average growth rate may be identified as statistically significant in a country where the underlying growth process has low volatility so that even small changes seem to be big when viewed through the "statistical" lens. At the same time, a 4 percentage points change can be dismissed in another country where the growth process is inherently more unstable so that important changes appear as "random" from a statistical perspective.

To understand the practical consequences of using the BP methodology for our purpose (extracting trend growth), we implemented a statistical approach based on a standard F-test (Zeileis et al. [44, 43]) and found a statistically significant break for Canada in 1979 with its average real GDP p.c. growth rate changing from 2.7% per annum between 1951 and 1979 to 1.3% p.a. for the 1980-2015 period. We also found only one break for China, in 1977, i.e. we completely missed seven shifts in the Chinese trend growth rate, illustrated in Figure 2.3, which are not only economically large (over 3% points changes each) but, as discussed below, also coincide with major events in the Chinese economic history.

This "low power" issue inherent in the statistical methodology is widely recognized in the literature, e.g. Bai and Perron [10] confirm the presence of "true negatives" through Monte Carlo simulations. Jones and Olken [28] explicitly recognize that the sets of break dates they identify are "conservative", while Berg et al. [12] complement the statistical tests with economic criteria to go from statistical breaks to economically meaningful growth spells by removing some irrelevant breaks.

The "filter" approach avoids this "low power" issue by looking specifically for economically meaningful changes in the medium/long term growth rate, found by systematically applying a set of researcher-defined rules to growth data. For instance, Hausmann et al. [23] identify growth accelerations as "increases in per-capita growth of 2 percentage points or more, [...] sustained for at least eight years and [such that] the post acceleration growth rate [is] at least 3.5 percent per year." Another example is Hausmann et al. [24], who define growth collapses as "intervals that start with a contraction of output per worker and end when the value immediately preceding the decline is attained again". Clearly, the main disadvantage of the filter approach is the lack of a common framework, which identifies up and down-shifts in a consistent manner.

2.2.2. *The original Fit & Filter (FF).* A recent paper by Kar, Pritchett, Raihan and Sen [29] summarizes the shortcomings of both approaches and proposes to combine them in order to overcome their limitations while preserving their advantages. The authors call the result "Fit & Filter" (FF) because the approach "involves the best fit of the BP method to the data in the first stage, and the application of a filter to the breaks identified in the first stage in the second stage." Hence, FF overcomes the "low power" of the statistical approach by not using its second step (the statistical tests), while providing a unified way of identifying both economically meaningful up and down-shifts.

Another important advantage of the original FF is that, unlike the standard statistical and filter approaches, it takes into account the nature of the previous shift: a first candidate break is classified as "genuine" if the average growth rate before and after the break changes by at least 2% points. For any subsequent break, the filter distinguishes between a break in the same direction (e.g. acceleration after acceleration), in which case a 1% point change is enough for significance, and a break in the opposite direction (e.g. deceleration after acceleration) where the shift has to be at least 3% points large to be qualified as genuine.

Recognizing this nonlinearity in growth dynamics is important because of the reversion to the mean phenomenon (Easterly et al. [15], Pritchett & Summers [34]) - the idea that it is much easier for countries that have experienced a trend up-shift in the past, to then experience a trend down-shift, i.e. to revert back to the world average growth rate, rather than experience yet another up-shift. Hence a further acceleration in their trend growth rate of even as little as a 1% point is already a substantial achievement. A similar argument would hold for down-shifts.

To help the reader understand how the FF approach works in practice, here is a concrete example from the original paper [29]:

> In the case of Brazil, the first step identifies four candidate break years: 1967, 1980, 1992 and 2002. In 1967, growth accelerated from 3.7% (for 1950–1967) to 6.3% (for 1967–1980). Since this is the first potential break and is above the 2% threshold, we conclude that it as a genuine break. In 1980, growth decelerates from 6.35% to -1.1% (for 1980–1992), a deceleration of 7.4% and easily passes the "deceleration following acceleration" threshold of 3%. In 1992, growth accelerates from -1.1% to 1.4%, a change of 2.5%. However, as this is an acceleration following a deceleration, it would have to be above 3% in order to pass the filter and hence we do not

> include 1992 as a "genuine" growth break. In 2002, growth accelerated again, this time to 2.5% and since this was an acceleration following a previous candidate acceleration it only had to pass the 1% threshold.

KPRS [29] document that FF achieves a substantial improvement over the statistical method in identifying a larger number of "true negatives", especially in developing countries where the volatility of growth is itself a consequence of a trend growth process with many shifts, and in omitting the "false positives" in developed countries with smooth trend growth paths. Furthermore, the breaks identified often seem to coincide with major events in the economic history of the respective countries. Hence, it seems that FF is fully appropriate as a method of extracting trend growth as a sequence of medium/long term averages taken over periods that are historically meaningful, and such that shifts in trend growth are economically significant.

Despite this, the original FF has two issues which became apparent as we tried to generalize it and employ for our purpose. Both arise because of the way in which FF uses the first step of the BP methodology, i.e. the "Fit" part. As explained above, this first step simply finds the optimal location of a given number of breaks (from one up to a maximum allowed/possible) in a given time series by minimizing the residual sum of squares (best fit). The statistical approach then uses these sets of optimal dates and their associated residual sums of squares sequentially in the second step (the statistical tests). By contrast, there is no sequential testing in the FF: it only uses the optimal set of dates identified for the maximum allowed and hence the choice of this maximum matters a lot.

The authors assume 8 years between breaks and simply "postulate that a country with: (i) Forty years of data, can have a maximum of two breaks. (ii) More than 40 years and up to 55 years, can have a maximum of three breaks. (iii) More than 55 years, can have a maximum of four breaks." However, with five more years of data and assuming a minimum of 5 years between breaks instead of 8, what maximum number should we postulate to apply the filter?[3]

Retaking the example of Brazil. Postulating seven gives 1956, 1962, 1967, 1973, 1980, 1987, and 1992 as potential breakpoints, all of which pass the filter. Choosing eight as the maximum yields 1956, 1962, 1967, 1973, 1980, 1992, 2003, 2010. However, now 1992 and 2010 miss the filter thresholds.

This example illustrates the two crucial issues with the original FF:

[3]We use the Penn World Table version 9.0 (Feenstra et al. [16]) extended to 2015 with IMF World Economic outlook data, while KPRS use PWT version 7.1 that stops in 2010. Also note that we use real GDP p.c. data while KPRS employ GDP p.c. in Purchasing Power Parity.

(1) the choice of the maximum matters for whether we identify a break date as genuine or not: 1992 is a genuine break point if we assume a maximum of seven break dates, but becomes fake if we raise this maximum to eight;

(2) the final set of dates identified as genuine by FF is not necessarily optimal: if FF identifies six out of eight breaks as genuine, the locations of the six genuine breaks are not necessarily such that the residual sum of squares is minimized (best fit) over all possible sets of *six* break dates since they were selected as part of the eight-dates set that gives the best fit among all sets of *eight* dates. These are two different optimization problems and the optimal set of m break dates is not necessarily a subset of the optimal set of $m+1$ break dates (cf. Bai and Perron [9] for the dynamic programming algorithm used to solve these problems). This issue creates a disadvantage for the FF as compared to the statistical/BP methodology where the final set of break points identified is always optimal since only optimal sets are used in the sequential testing and if a set is rejected, *all* the dates within this set are rejected and the non-rejected alternative is just another set of optimally located dates.

2.2.3. *The iterative Fit & Filter (iFF).* In order to make FF robust to these issues, we propose an iterative algorithm that builds on the original FF and that we therefore call the "iterative Fit & Filter" (iFF). iFF can be easily programmed in any standard statistical software package by following the steps described in the insert on the next page. The computer code that implements it in R is available on request.

The researcher no longer has to postulate any maximum number of breaks. The only choice parameters are the minimum trend growth duration and the filter, which, as we discussed in section 2.1, should depend on how trend growth is defined for the purpose of the research question.

Given the specified minimum duration δ, **Step 1** simply determines the maximum possible number of breaks from the length T of the time series and calls it m_1. We then search for the set of m_1 dates that minimizes the residual sum of squares (**Step 2**) and such that the minimum number of years between any two trend shifts is δ, i.e. we take averages over at least δ years.

We then use the identified candidate shift dates to compute the candidate trend growth process and the set of candidate trend shifts (**Step 3**). We check whether or not all trend shift dates pass the filter threshold(s).

If yes (**Step 4.1**), we are done: we have found the trend process that satisfies our definition of trend growth - conditions (1) and (2) in section 2.1. The optimal trend shift dates delimitate the periods over which the averages have to be taken when extracting the trend from growth time series.

Algorithm 1 Iterative Fit & Filter (iFF)

Notation: Let $\lfloor x \rfloor$ denote the largest integer that does not exceed x.
For any set of trend shift dates $\mathscr{T} = \{T_1, ..., T_m\}$, the residual sum of squares is computed as:

$$RSS(\mathscr{T}) = \sum_{j=1}^{m+1} \sum_{t=T_{j-1}+1}^{T_j} [g(t) - \tau(t)]^2$$

where:

$$\tau(t) = \frac{1}{D_j} \sum_{s=T_{j-1}+1}^{T_j} g(s) \text{ for } t \in T_{j-1}+1, ..., T_j,\ j = 1, ..., m+1 \tag{2.3}$$

and $D_j = T_j - T_{j-1}$ is the jth *trend growth duration* - number of years for which the country grows at the trend growth rate at which it started growing in period $T_{j-1}+1$.

Step 1: Determine the maximum possible number of trend shifts m_1. Given the length of the time series T and the minimum trend growth duration δ, the growth time series can be divided into at most $\lfloor T/\delta \rfloor$ segments, hence:

$$m_1 = \lfloor T/\delta \rfloor - 1$$

Step 2: Let $\hat{\mathscr{T}} = \{\hat{T}_1, ..., \hat{T}_{m_1}\}$ be the set of m_1 shift dates that minimize the residual sum of squares:

$$\hat{\mathscr{T}} = \arg\min_{\mathscr{T}} RSS(\mathscr{T})$$

over all possible sets of m_1 trend shift dates $\mathscr{T} = \{T_1, ..., T_{m_1}\}$ such that $T_j - T_{j-1} \geq \delta$ for all $j = 1, ..., m_1 + 1$. In practice, this set can be found by using the dynamic programming algorithm described in Bai and Perron [9].

Step 3: Use the optimal trend shift dates $\hat{\mathscr{T}}$ and eq.2.3 to compute the trend $\{\tau(t)\}_{t=1}^{T}$ and the set of trend shifts: $\{\Delta\tau(t)\}_{t\in\hat{\mathscr{T}}}$.

Step 4.1: If all trend shifts satisfy the threshold(s) of the filter, i.e. for all $t \in \hat{\mathscr{T}}$.

$$|\Delta\tau(t)| \geq F$$

we have found an optimally placed set of trend shift dates such that all resulting trend shifts are economically significant. $\{\tau(t)\}_{t=1}^{T}$ computed in Step 3 is the trend.

Step 4.2: While at least one of the trend shifts is not economically significant, we re-iterate Steps 2 and 3 with:

$$m_{k+1} = m_k - 1$$

instead of m_1 until either we end in Step 4.1 with an optimally placed and economically significant set of m_k trend shifts $\hat{\mathscr{T}}$, or $m_{k+1} = 0$ and we conclude that there are no trend shifts and simply compute the trend as the average growth rate over the T periods.

If not (**Step 4.2**), there is at least one trend shift that is not economically significant. To see why we need to re-iterate steps 2 and 3 in this case, suppose that 4 out of 5 trend shifts satisfy the threshold(s). The only thing that we can conclude at this point is that there is no way of segmenting our growth time series with 5 trend shifts that are both optimally placed and economically significant. The four trend shifts that happen to be economically significant are not necessarily optimally placed because their location in step 2 was determined by minimizing the residual sum of squares over all possible sets of *five* trend shift dates. To determine the optimal location of four trend shift dates, we would need to minimize the residual sum of squares over all possible sets of *four* trend shift dates, i.e. re-do step 2 with $m_2 = 4$.

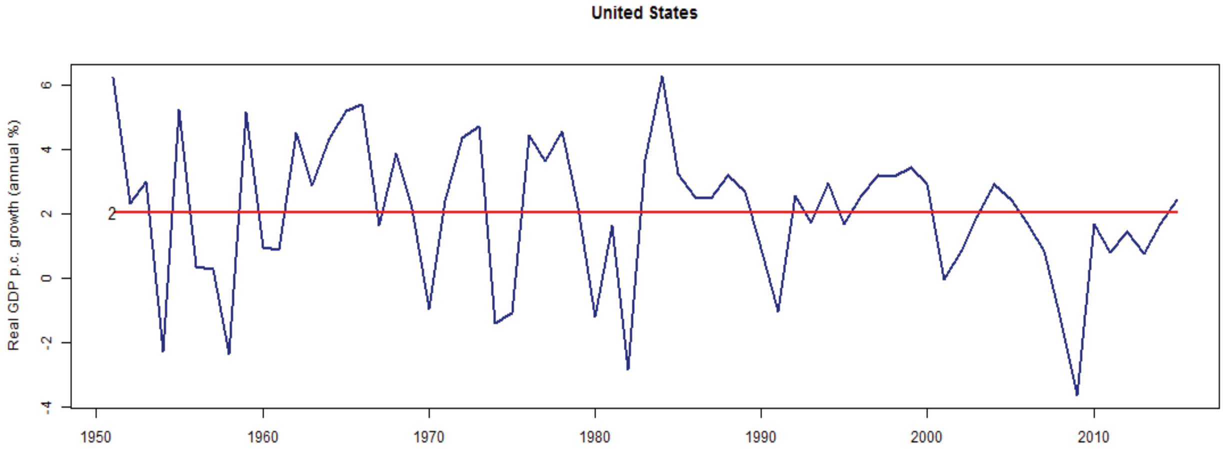
We re-iterate our search as long as a trend process with all trend shifts satisfying the economic filter is not found. Intuitively, in each iteration k, we ask the following question: is it possible to divide our growth time series so that m_k trend shifts are placed optimally (**Step 2**) and are economically significant (**Steps 3 & 4**)? If no trend shift dates are identifed as economically significant, we simply conclude that the country experiences no trend shifts in the sample over which we observe it, and therefore our best guess of its trend growth rate over this sample is the full sample growth average.

2.3. **iFF in practice: trend growth & economic history.** We now examine some real world examples of what iFF applied to growth time series data yields. Annual real GDP p.c. growth rates are constructed using the *Penn World Table* (PWT) version 9.0 (Feenstra et al. [16]) and extended to 2015 with the IMF *World Economic Outlook* (WEO) data. Our sample contains twenty developed countries and we use developing when referring to any country that is not developed (i.e. our developing countries include newly industrialized countries, emerging markets, frontier markets, and least developed countries).[4]

Table 7 in the Appendix summarizes the most recent (as of 2015) trend growth rate and the last trend shift date and magnitude for all 153 countries in our sample, as well as the hazards (conditional probabilities) of trend up and down-shifts which are the focus of the next section. Figures 2.1 to 2.3 illustrate the complete trend growth paths (red) for the USA, France, and China.

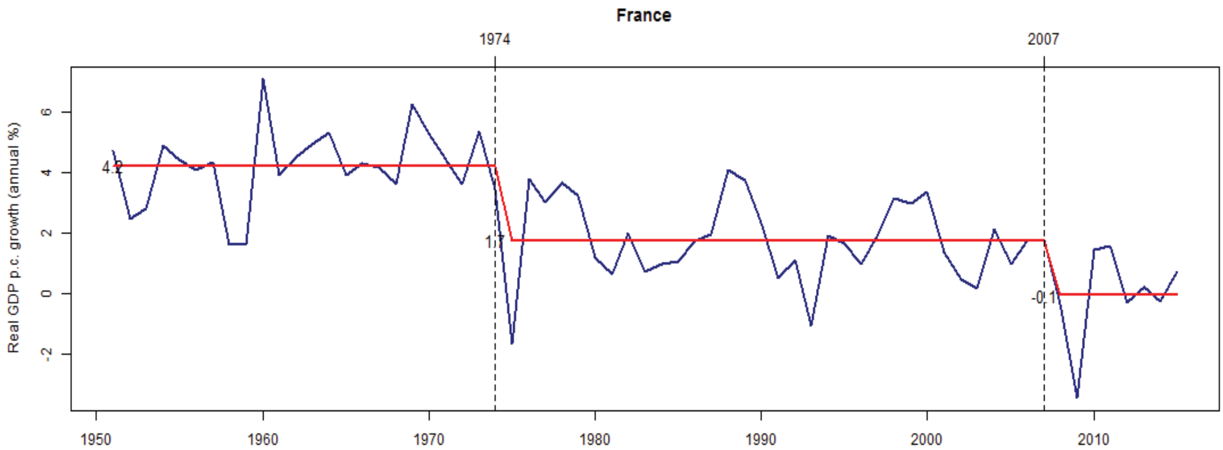
[4]PWT version 9.0 provides data for 182 countries, up to and including 2014. Data goes back to 1950 for some countries. The database is freely accessible at http://www.rug.nl/research/ggdc/data/pwt/pwt-9.0 and fully described in Feenstra et al. [16]. To construct our real GDP p.c. time series, we divide rgdpna (Real GDP at constant 2011 national prices (in mil. 2011US$)) by pop (Population (in millions)). We remove 28 countries with population less than 600,000 in 2014 and the State of Palestine because it is absent from major datasets like the IMF WEO and the World Bank World Development Indicators (WDI) that we employ below. The set of developed countries includes: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Ireland, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, United Kingdom and the United States.

Figure 2.1 Trend growth in the United States (1951-2015)



Notes: Trend growth (red) extracted from annual real GDP p.c. growth data (blue) using iFF.

Figure 2.2 Trend growth in France (1951-2015)



Notes: Trend growth (red) extracted from annual real GDP p.c. growth data (blue) using iFF.

Between 1951 and 2015, trend growth in the USA, as well as Australia, Canada, Sweden and the UK, can be summarized by a single rate of around 2% p.a. At the same time, other developed countries like France, Germany, Italy, Spain etc., and, in particular, many developing economies have experienced more interesting trend growth dynamics that often coincide with important country-specific historical and political developments.

For instance, in France (figure 2.2), 1974/75 marks the end of a thirty years period known as *"The Glorious Thirty"* (*"Les Trente Glorieuses"*, cf. Fourastié [18] who coined the term or Lejeune [31] for a more recent reassessment of the period). Damaged by the two World Wars, France experienced a period of "catch up" growth driven by the reconstruction and the industrialization of the country, rising productivity and consumption levels. However, as this model of growth reached its limits, the country, hit by the 1973 oil shock, entered a period of stagflation, rising unemployment, and slower productivity growth. Trend growth per capita dropped from 4.2% p.a. to 1.7% p.a.

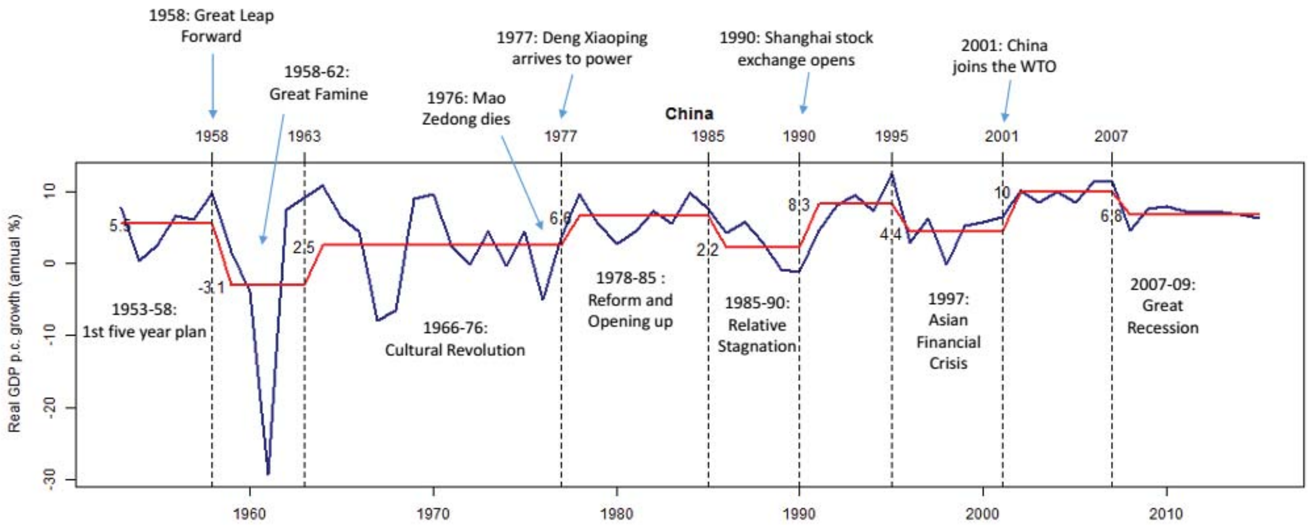
In France, as in Finland, Austria, Ireland, Italy, Greece, Cyprus, Norway and Spain (cf. Table 7), 2007/2008 appears as a down-shift in trend growth, while in other developed economies it is "only" a very large negative fluctuation around a per-existing trend. This may be because this pre-existing trend growth rate was already very low, e.g. Portugal has been growing at close to 0% since 2001, or because the country recovers from the Great Recession relatively quickly and is not as harshly hit by the 2011/12 recession, e.g. Germany.

Note that as time passes and iFF is fit on new enlarged samples, the trend shift dates (especially the latest ones) may be re-assessed. Indeed, with hindsight it will become more obvious whether or not 2007 was a watershed in the economic history of France. As of 2015/16, it seems that the country experienced a downward sustained shift in 2007 not only because of the global financial crisis - although this has certainly been an important catalyst. The profound need for structural reforms in France and a rising level of domestic discontent have rendered the country vulnerable to external shocks. France needs to "change [its] model", to paraphrase the title of a recent book by Aghion, Cette and Cohen [2] in which the authors discuss a set of reforms that could help France become an innovation-driven economy and experience an up-shift from its current 0% trend growth rate.

Another interesting example is China.

After a period of restoration from WWII (1949-1952), the Communist Party of China (CPC), under the leadership of Mao Zedong, launched the first five-year plan in 1953. Modeled after the Soviet example and aided by Soviet planners and engineers, the CPC re-organized industries into cooperatives and farmers into socialized collective units. The main goal of the plan was to achieve high economic growth with a particular focus on developing heavy industries (steel, concrete, iron, machinery, ...). Investment in the industrial sector was financed by extracting surpluses from agriculture where prices were set artificially low. Although, the economy did expand at a trend growth rate of 5.5% p.a., an important sectoral imbalance emerged, and in 1958, the CPC decided to abandon the Soviet model and instead to take a "great leap forward" in the production of all sectors simultaneously.

Figure 2.3 Trend growth in China (1951-2015)



Notes: Trend growth (red) extracted from annual real GDP p.c. growth data (blue) using iFF.

Collectivization was pushed further with the prohibition of private plots and the establishment of communes. Decision-making and planning were decentralized. The construction of Soviet-like large and capital-intensive plants was pursued but at a slower tempo and now complemented with locally built and run, small-scale, low-technology projects. These "backyard" projects yielded substandard products while diverting an important proportion of farm labour, and together with the inefficiency of the communes, the withdrawal of the Soviet financial and technical support, and several natural disasters, resulted in what is known as the "Great Famine" - a substantial disruption of China's agriculture which starved to death at least 15 million people (unofficial estimates range higher, between 20 and 30 million) between 1959 and 1962.

Indeed, although the CPC started to repel the "Great Leap Forward" program already in 1960 with private plots being returned to the farmers, the communal system being reduced, unemployed workers and investment being transferred from industry to agriculture; it is only in 1963 that the agricultural situation had sufficiently improved and some resources started being redirected back to the industrial sector.

Another consequence of the disruption produced by the "Great Leap Forward" was the appearance of a group of politicians who recognized that China needed to switch to a model of development where material incentives play a greater role, and against whom Mao Zedong initiated the Cultural Revolution in early 1966. Political instability continued until Mao's death in 1976 and Deng Xiaoping's arrival to power in 1977.

Xiaoping announced a modernization program which pushed the country onto a new development path of "reform and opening up" ("*Gaige Kaifang*") from 1978 onwards.

Indeed, 1978 is very often considered as a watershed in the economic history of modern China, “the year when China started economic reform” (Zhu [45]). The goal was not to eliminate state planning and control, but to increase the role of material incentives by introducing market mechanisms into the system. The program aimed at expanding foreign trade (by encouraging exports, easing negotiations and cooperation with foreign firms and legalizing trading and credit arrangements) and eliminating existing deficiencies and distortions (e.g. between light and heavy industries).

Zhu [45], who implements a growth accounting exercise to decompose the sources of Chinese growth before and since 1978, shows that in the before period, all growth was due to physical and human capital accumulation, financed by massive government investment and a rise in education levels. On the contrary, since 1978, a rise in productivity became the main driver of growth.

Productivity in agriculture was stimulated through a substantial rise in official agriculture prices and the creation of the “household responsibility system” in 1979. Under the latter, farmers had to sell a certain amount of grains at official prices to the government, but could then transact anything beyond the quota at market prices and for their own enrichment.

The results were considerable: fig. 2.3 shows that the economy expanded at 6.6% p.a. and per capita. Trade increased from 8.5% of GDP in 1977 to 23% in 1985. All sectors were expanding except for manufacturing, whose value added as a percentage of GDP even fell from 39.3% in 1977 to 34% in 1985, because heavy industry was purposefully restrained.[5]

The reforms were introduced gradually, first in a few localities, then, if successful, nationally, and completed by 1984 when most households were under the responsibility system, and most communes had been dissolved. The efficiency gains “from workers using the same technology with a much more rewarding set of incentives, were largely exhausted” by 1984 (Zhu [45]), and a period of relative stagnation began with trend growth shifting down to 2.2% p.a. in 1985.

A new liberalization wave emerged around 1990 with trend growth shifting up to 8.3% p.a. Government interventions were further reduced, markets for agricultural inputs and outputs further liberalized and incentives for the adoption of new technologies set in place. The Shanghai and Shenzhen stock exchanges opened in 1990 and 1991 respectively. The “open door” policy was introduced in 1992 with the aim of creating a legal basis for Chinese-foreign joint ventures. Special economic zones were introduced to facilitate the influx of foreign investment.

[5]Figures quoted in this passage are taken from the World Bank Development Indicators.

Although China was less affected by the Asian Financial crisis than other economies, e.g. Indonesia and Thailand which experienced trend down-shifts to negative growth rates in 1996, the Chinese trend growth rate did slow down to 4.4% p.a. in 1995. Indeed, foreign direct investment as a percentage of GDP fell from 6% in 1994 to 3.2% in 2000 and monetary conditions were tightened with the annual broad money growth rate falling from 31.5% in 1994 to 12.3% in 2000.

The last up-shift in China's trend growth rate to 10% p.a. in 2001 coincides not only with a global economic recovery but also China's entry into the World Trade Organization, which "introduced international economic laws [into the country] and ushered a period of rapid regulatory reform by creating agencies such as the China Banking Regulatory Commission (CBRC) to govern increasingly globally integrated markets" (Yueh [42]).

Recently, there has been a lot of debate in the press and the academic literature (e.g. Pritchett & Summers [34]) about whether or not the Chinese economy is slowing down. Our analysis indicates that China, hit by several natural disasters (the 2008 Chinese winter storms and floods in the South, the Sichuan earthquake) and the Global Recession (e.g. Chinese trade fell from 64.8% of GDP in 2006 to 41.2% in 2015), has already experienced a down-shift in trend growth in 2007 and is currently growing at 6.8% p.a.

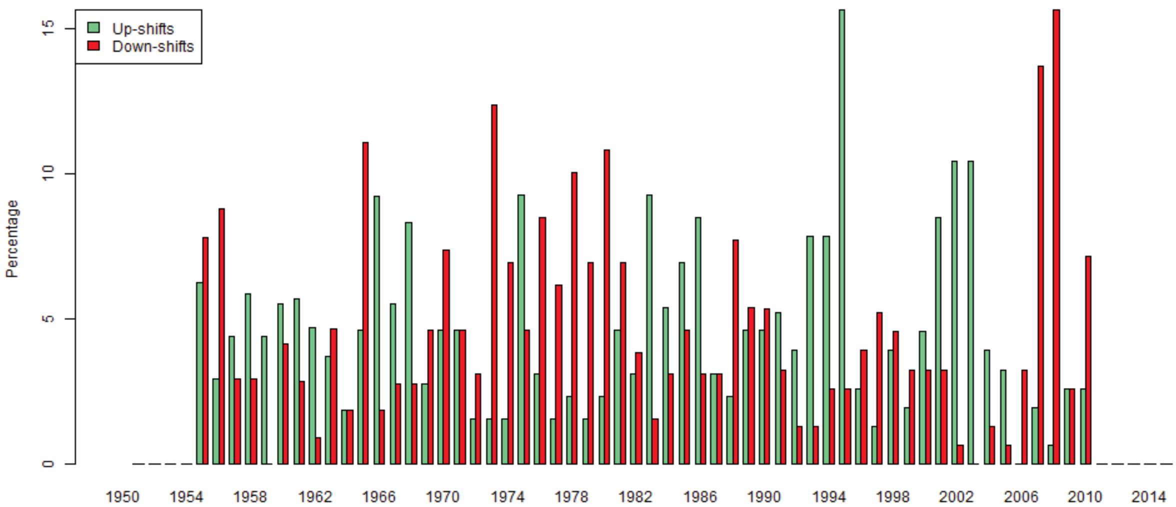
Whether a further slowdown will happen in the future is an open question and we shall try to contribute to the ongoing debate below, in section 4.3.

These examples suggest that iFF inherits from the original FF the ability to identify in a systematic way important episodes in the economic history of a country and could therefore be a useful tool for economic historians, many of whom still often rely on their judgment or arbitrary time periods when presenting and interpreting summary statistics. For instance, to decompose the 1978-2007 period into subperiods, Zhu [45] simply takes three ten years long periods: 1978-1988, 1988-1998, and 1998-2007, while our analysis suggests a rather different decomposition of the 1978-2007 period into economically and historically meaningful subperiods. In future work, iFF could therefore be employed to undertake a much more thorough economic history analysis for a larger number of countries.

3. Trend Growth Durations & Shifts: Stylized Facts

Although the previous examples illustrate the great variety of trend growth dynamics within and between countries, it is also important to try to establish some stylized facts about the trend growth processes identified. In this section, we look at the temporal

Figure 3.1 Temporal distribution of trend shifts



Note: Percentages of countries experiencing up and down-shifts in trend growth p.a.

and spatial distributions of *trend growth shifts*, and the distribution of *trend growth durations* in developed versus developing countries.

3.1. **Trend growth shifts.**

3.1.1. *Temporal distribution.* Although we have growth data for 153 different countries, these countries are observed over different periods of time between 1950 and 2015, so that the effective number of countries in our sample varies over time.[6]

Hence, the number of trend shifts happening in a given year is not directly comparable over time. Instead, in order to investigate the temporal distribution of trend shifts, Figure 3.1 shows the percentage of countries experiencing trend up and down-shifts each year.

The earliest and latest shifts happen respectively in 1955 and 2010 since we assume a minimum trend growth duration of 5 years. The alternation between red bars dominating green ones and vice versa suggests that up and down-shifts do not coincide. Indeed, the correlation between the percentages of up and down-shifts each year is

[6]For instance, data for all post-Soviet nations only starts in 1990 (growth data from 1991). These countries have so far been almost always excluded from similar studies on the grounds of not sufficiently long time series - e.g. Hausmann et al. [23] require at least 20 data points, Pritchett & Summers [34] exclude all countries with "less than 25 years of data". We believe it is important to integrate this group of countries into our study, not only because we now do have 25 years of growth data for them, but also because their post-Soviet experiences certainly contain a lot of valuable information for helping us understand what affects trend growth durations & shifts.

-0.12; not very big but negative, possibly indicating the presence of systemic trend growth spillovers that could be investigated in more details in future work.

Earlier studies (e.g. Ben-David & Papell [11]) have found that for developed countries most up-shifts take place in the 1950s and the 1960s during the postwar reconstruction period, which coincides with a significant liberalization of trade and the creation of institutions such as Bretton-Woods and GATT, while most down-shifts take place in the early 1970s, with the first oil price shock in 1973 acting as an important catalyst.

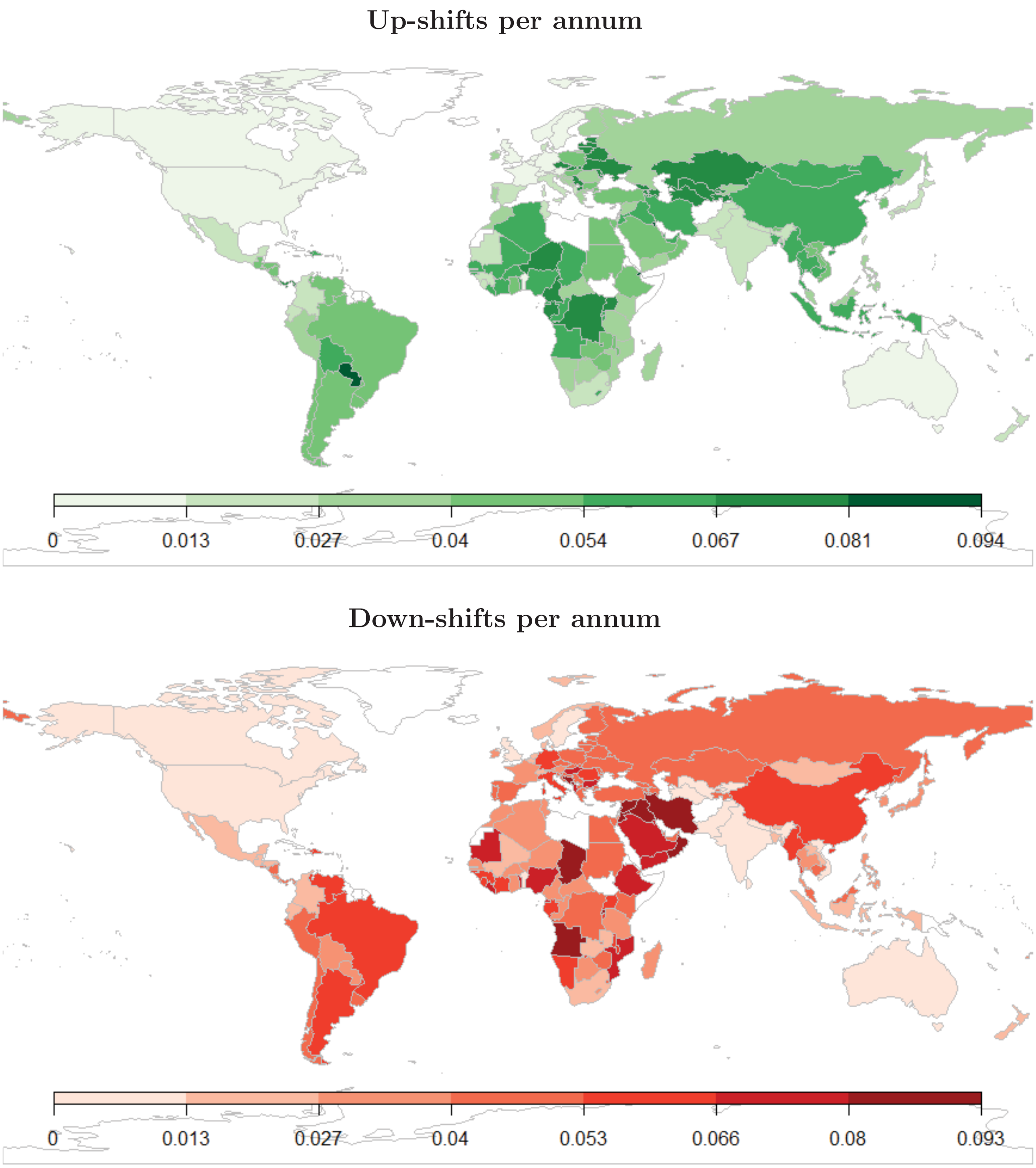
Our research confirms and extends these previous findings. All twenty developed countries are observed between 1950 and 2015 and, overall, experience 11 up-shifts and 31 down-shifts. Most up-shifts (8 out of 11) happen during the 1950s and 1960s, and 35% of all down-shifts take place in the 1970s. However, a novel finding is that 32% of all down-shifts happen in the 2000s highlighting the magnitude of the impact of the Great Recession in the developed world.

Many Latin American countries experience trend down-shifts in the late 1970s/early 1980s, e.g. Venezuela in 1977, Argentina and Brazil in 1980, Mexico and Chile in 1981 (cf. Diaz-Alejandro [14] for a thorough analysis of the Latin American debt crisis). Most down-shifts of the late 1990s are related to the Asian Financial crisis: Thailand and Indonesia in 1996, Malaysia and Singapore in 1997...

The 15% of up-shifts in 1995 mostly come from countries that were part of the Soviet Bloc - Armenia, Azerbaijan, Belarus, Estonia, Georgia, Kazakhstan, Kyrgyzstan, Latvia, Lithuania, Moldova, Uzbekistan, Serbia, Slovakia, Slovenia, Macedonia ... which started to recover from the disruptions in their economies produced by the collapse of the Soviet Union in 1991. Another important wave of up-shifts happens in the early 2000s. Some are further up-shifts in emerging eastern Europe (Tajikistan & Ukraine in 2001, Armenia in 2000...), others are recoveries from the Asian crisis (Indonesia and Thailand 2001). Many commodity exporters experience up-shifts in 2002/2003 (Argentina, Peru, and Colombia in 2002, Bolivia and Venezuela in 2003) as a recovery from a period of historically low commodity prices between 1998 and 2002 which led to significant falls in tax revenues and important economic disruptions in these countries (cf. Tenreyro [40] for a retrospective analysis of the 2001-2002 Argentine crisis and Spatafora and Samake [39] for an empirical investigation of how commodity prices and fiscal outcomes are related).

The late 2000s, especially 2007/2008, stand out as the most important years of trend growth down-shifts in modern history. Of course, we should not forget that this is close to the end of the sample and results could change later on, with hindsight. However, this finding seems plausible given the magnitude of the growth disruptions provoked by the Great Recession in both developed and developing countries.

Figure 3.2 Spatial distribution of trend growth shifts



Note: Countries not in sample are in white.

3.1.2. *Spatial distribution.* Each country in our sample has between 25 and 65 years of growth data. Hence, similarly to the number of trend shifts per annum, the numbers of trend shifts per country are not directly comparable. Instead, to investigate the spatial distribution of trend up and down-shifts, Figure 3.2 illustrates the respective numbers of shifts per annum.

Several interesting observations emerge. First of all, developing countries are more prone to both up and down-shifts than developed ones. This finding is not new. In his seminal contribution, which spurred researchers to pay much more attention to within country growth dynamics, Pritchett [33] already argued that "a single time trend does not adequately characterize the evolution of GDP per capita in most developing countries".

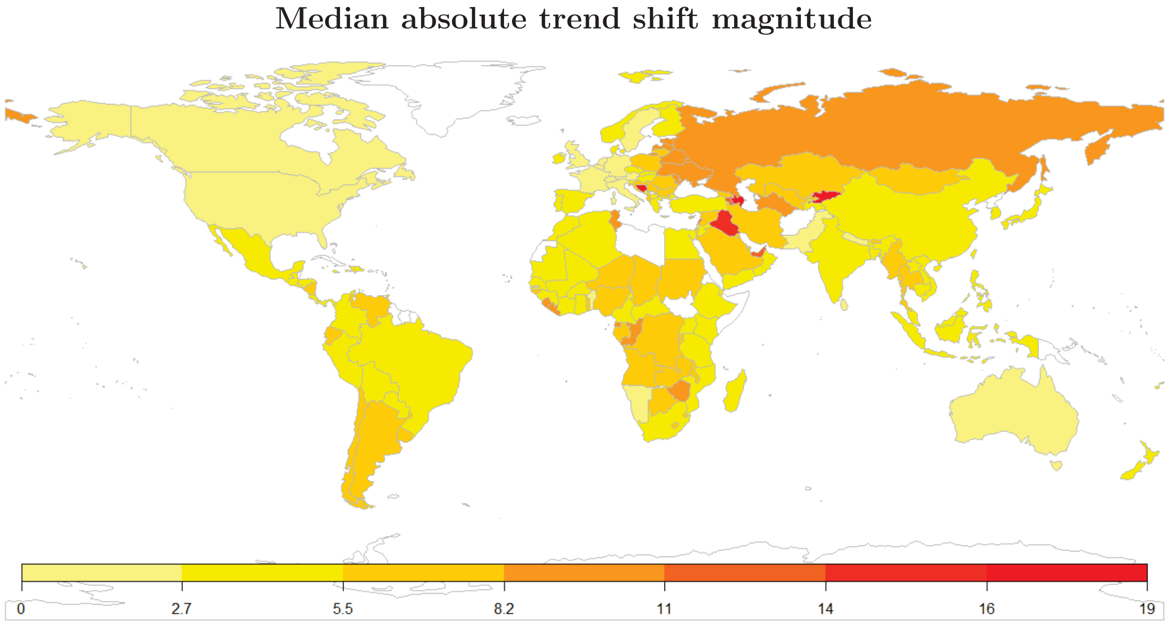
The correlation between the numbers of up and down-shifts p.a. is 0.33, suggesting that for some countries trend growth is unstable in both directions, and that, at least to some extent, all countries are capable of both up and down-shifts. In particular, the figures buttress the findings of Frances, Paap and van Dijk [19] who examine the question of whether Africa is less capable of growth than Latin America or Asia. They implement a data-based classification of countries into clusters and find that one third of African countries are not assigned to the low growth cluster. Hence, it is wrong to aggregate and simply label Africa as the "lost continent". Figure 3.2 indeed shows that although some African countries do exhibit very large numbers of down-shifts p.a., this is not the case for all the continent. Moreover, many African countries also exhibit a significant number of up-shifts and are comparable to Latin American and Asian countries in terms of numbers of up and down-shifts. If anything, it seems that there is more heterogeneity in both up and down-shifts p.a. in Africa than on any other continent.

Middle East countries appear as very prone to down-shifts because of the numerous conflicts that have taken place in these countries over the past half century.

One potential caveat to bear in mind when interpreting our findings, is that some of our up-shifts are from negative growth to less negative growth, while some down-shifts are from positive to less positive growth. In this simple approach, we also do not distinguish between shifts of different magnitudes. Figure 3.4 therefore complements the analysis by showing the spatial distribution of the median absolute trend shift magnitude for each country in our sample. Once again, it seems that overall developing nations experience much larger swings in their trend growth paths in both directions. The median absolute trend shift in a developing country is 5.45% points against a mere 2.3% pts. for developed economies.

Note that the relatively large trend shift magnitudes of many post-Soviet nations may be directly due to the fact that we have growth data for them only since 1991, a period that coincides with a particularly turbulent part of their histories after the collapse of the Soviet Union. Their large up-shift intensities exhibited in Figure 3.2 are also, at least to some extent, the result of recovering from a period of very negative growth rates in the first half of the 1990s.

Figure 3.4 Spatial distribution of trend shift magnitudes



Note: Countries not in sample are in white.

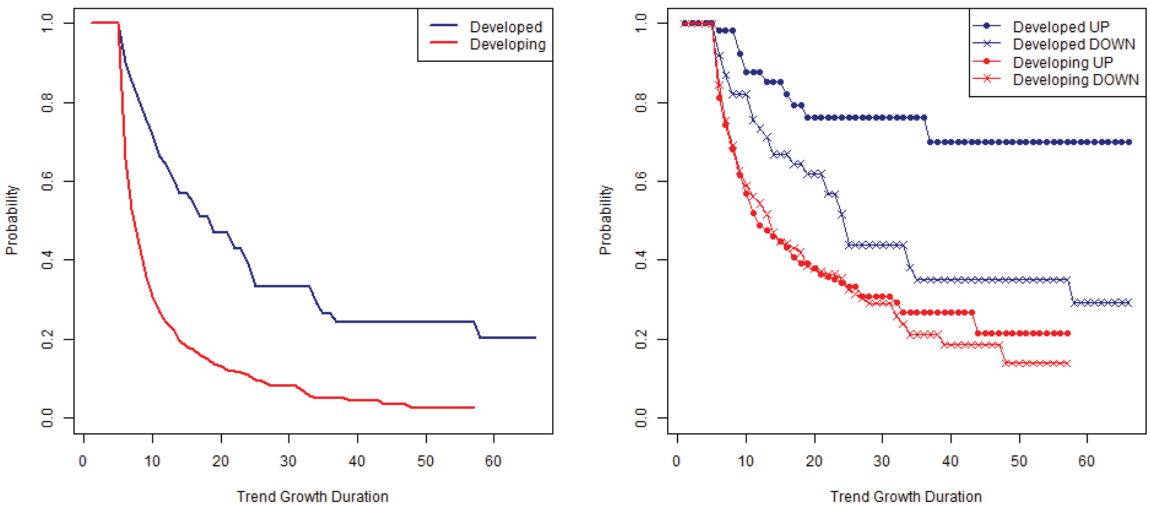
3.2. **Trend growth durations.** In practice, the much greater instability of trend growth in developing countries documented above implies that the number of years over which it makes economic and historical sense to take medium/long term averages of growth rates - *trend growth durations* - in these countries are shorter.

To make this more precise, let's think of the *trend growth duration* - number of years between two consecutive *trend growth shifts* - as a discrete random variable that takes values in $\{\delta, \delta+1, \delta+2, ...\}$.

Our data consists of trend growth episodes, each starting in $T_{j-1}+1$ (the year after the last trend growth shift or the beginning of the sample if $T_{j-1}=0$, where 0 is the year when GDP p.c. data is first observed for the country so that growth rates are computed from year 1) and ending in T_j with trend growth shifting either up or down, or with the end of the sample if $T_j = T$. Hence, each trend growth episode has a certain duration $D_j = T_j - T_{j-1}$. When $T_j = T$, the duration is censored since we do not know when the current trend growth episodes will end. The only thing we know is that they have already lasted for $\widetilde{D}_m = T - T_{m-1}$ years, m being the number of trend growth shifts.

Treating our data as a random sample collected from the population of trend growth episodes, the left panel of Figure 3.5 compares the probabilities that an developing (red) versus a developed (blue) country has a trend growth duration of at least d years:

Figure 3.5 Trend growth survivor functions



Notes: Developing countries trend growth survivor functions estimation based on 671 trend growth episodes and 629 trend growth shifts. For developed countries the respective numbers are 62 and 42.

$$S(d) = \Pr(D_j \geq d) = \sum_{k=d}^{\infty} \Pr(D_j = k)$$

In survival/duration analysis, $S(d)$ is known as the *survivor function.*[7]

The comparison is stark: while the probability of having 10 years or more between two consecutive trend shifts in a developed country is 0.72, in a developing country it is as low as 0.31. In developed countries, half of the trend growth episodes last for at least 18 years ($S(18) = 0.5$), while in developing countries this number is around 7 years.

Also, note that 20% of all trend growth episodes from developed countries in our sample are censored at 66 because a number of developed countries experience no trend shifts between 1950 and 2015, i.e. we only know that these countries have been growing at the same constant trend growth rate for at least 66 years over which we observe them.

Since we have assumed $\delta = 5$, the probability of all trend growth durations lasting at least 5 years is one: $\Pr(D \geq 5) = 1$.

Thereafter, $S(d)$ is computed as:

$$S(d) = \prod_{k=\delta+1}^{d-1} (1 - \alpha(k)) \tag{3.1}$$

[7]Many great reference on discrete time survival analysis exist, for instance, Allison [6], Rodriguez [35], or Jenkins [27].

where $\alpha(d)$ is the *discrete-time hazard* - the conditional probability that a trend growth shift happens exactly d years after the last one, conditional on the current trend growth episode having already lasted d years:

$$\alpha(d) = \Pr(T_j = T_{j-1} + d | D_j \geq d) = \frac{\Pr(D_j = d)}{S(d)} \tag{3.2}$$

The intuition behind eq.3.1 is that for a trend growth episode to last for, say, at least eight years, the country must "survive" at the same trend growth rate for at least five years. This is always true since $\Pr(D \geq 5) = 1$. Conditional on this, it must survive the sixth year without trend shifts. This happens with probability $(1-\alpha(6))$. Given all this, if no shift happens in the seventh year - an event that has probability $(1-\alpha(7))$, the trend growth episode will have lasted 8 years or more: $S(8)$.[8]

Since, any trend growth episode can end with either a trend up-shift or a trend down-shift, the overall discrete hazard can be decomposed into two cause-specific hazards:

$$\alpha(d) = \alpha^U(d) + \alpha^D(d)$$

where

$$\alpha^U(d) = \Pr(T_j = T_{j-1} + d, \Delta\tau(T_j) > 0 | D_j \geq d) \tag{3.3}$$

$$\alpha^D(d) = \Pr(T_j = T_{j-1} + d, \Delta\tau(T_j) < 0 | D_j \geq d) \tag{3.4}$$

The right panel of Figure 3.5 divides the survivor functions into up and down-shift specific curves:

$$S^U(d) = \prod_{k=\delta+1}^{d-1} (1 - \alpha^U(k)) \tag{3.5}$$

and similarly for $S^D(d)$.

Interestingly, while in developing countries, one has to wait for about the same number of years before an up or a down-shift in trend growth occurs; in developed economies, we have to be much more patient before up-shifts than before down-shifts. Concretely,

[8] The non-parametric estimates shown in Figure 3.5 are constructed as follows (discrete version of the Kaplan-Meier non-parametric estimator):

$$\hat{S}(d) = \prod_{k=\delta+1}^{d-1} (1 - \frac{r_k}{n_k})$$

where r_k is the number of trend growth episodes lasting for k years, while n_k is the number of episodes that could potentially last k years, i.e. are "at risk" of ending k years after beginning. In survival literature, $\frac{r_k}{n_k}$ is often called the "exit rate".

Table 1: Trend growth in developing vs. developed countries

	Developing	*Developed*
Std. Growth*	5.3	2.5
Std. Trend Growth*	3.4	1.2
Trend Var. as % of Growth Var.*	41.4	29.5
Up-shifts p.a.*	0.046	0
Down-shifts p.a.*	0.044	0.015
Median absolute shift magnitude*	5.45	2.30
Pr(10 years or more between shifts)	0.310	0.719
Pr(10 years or more until up-shift)	0.568	0.877
Pr(10 years or more until down-shift)	0.590	0.821
Number of Countries	133	20
Number of Up-shifts	322	11
Number of Down-shifts	307	31

Notes: *Median across countries. Std. (standard deviations) in percentage points.

the probability that we will have to wait 10 years or more until observing a trend up-shift in a developing country is 0.57. This number for a down-shift is very close: 0.59. By contrast, in developed countries the respective numbers are 0.88 and 0.82 and, as illustrated in Figure 3.5, the difference between the two probabilities grows very quickly as we consider longer horizons. For instance, the probability that we will have to wait 20 years or more before observing an up-shift in a developed economy is still very high 0.76 and well above the probability of waiting the same time until a down-shift: 0.62.

The intuition behind these findings can be related to standard economic growth theories as follows. In the process of convergence towards developed-economy status, countries experiences a similar number of up and down-shifts. Once developed and located at the technology frontier, however, generating up-shifts becomes much more difficult: "catch-up" growth is no longer available and growth spurts have to either come from exogenous technical progress (neo-classical growth model, Solow [38]), or an increase in savings as a proportion of GDP (AK model, Romer [36]), or innovation (Schumpeterian model, Aghion and Howitt [3]). At the same time, down-shifts can still happen because of exogenous shocks, or as a direct consequence of growth slowing down due to convergence (think about the post WWII reconstruction period slowdowns in most European countries).

Finally, Table 1 summarizes some stylized facts from this section about how the growth processes differ in developing and developed economies.

Although, overall, growth is twice as volatile in developing countries as in developed ones, the trend is almost three times more volatile and therefore accounts for over 41% of the total growth variance against slightly less than 30% in developed economies. This corroborates recent research by Aguiar and Gopinath [4] which shows that "emerging markets are characterized by a volatile trend that determines the behavior of the economy at business cycle frequencies". The result implies that understanding the determinants of the trend growth dynamics in developing countries is more important than in developed economies even in the medium term.

Several conclusions emerge from assessing the overall characteristics of trend growth durations and shifts. The trend growth path is much more unstable in developing economies as a group and represents a higher proportion of the overall growth process. Developing countries experience more trend shifts with larger trend shift magnitudes. However, contrary to developed countries, where waiting for up-shifts takes longer, up and down-shifts in developing economies happen roughly at the same rate. Despite these stylized facts, figures 3.2 and 3.4 illustrate the vast heterogeneity in country experiences within groups, while the country-specific examples discussed earlier (subsection 2.3) suggest that an important amount of variation in the duration of trend growth episodes exists for a given country over time. This implies that a discrete divide into developing/developed is too simplistic and calls for a more systematic assessment of the domestic and external macroeconomic factors that make trend growth durations vary so much within and between countries.

4. Predicting Trend Growth Shifts

Section 2 developed a methodology (iFF) for determining the trend growth rate at which a country is currently growing by extracting the trend from growth time series as a sequence of medium/long term growth averages taken over economically and historically meaningful periods of time. The purpose of the present section is to address our second motivating question: *"How likely is trend growth to shift and in what direction?"*

4.1. **Econometric framework: a trend-shifting model of growth.**

We start by extending the conceptual framework introduced in section 2.1 to achieve a comprehensive description of trend growth dynamics.

Remember that we conceptualize growth $g(t)$ as a process that vibrates around a trend:

$$g(t) = \tau(t) + c(t) \tag{4.1}$$

The cycle $c(t)$ is a zero-mean transitory fluctuation and the trend $\tau(t)$ is defined as the average growth rate between two consecutive trend growth shifts:

$$\tau(t) = \frac{1}{D_j} \sum_{s=T_{j-1}+1}^{T_j} g(s) \text{ for } t \in T_{j-1}+1, ..., T_j,\ j = 1, ..., m+1 \tag{4.2}$$

where $D_j = T_j - T_{j-1}$ is the duration of the trend growth episode that starts in $T_{j-1}+1$.

The trend is subject to competing domestic and external forces, summarized in the vector $\mathbf{x}_{t-1}$, which, if strong enough, can shift the trend up or down at time t and make growth vibrate around a new higher or lower level from $t+1$ onwards. In order to rule out a reverse effect from the trend shift in year t to the level of the time-varying variables in year t, we only use time $t-1$ information to predict time t trend shifts.

In particular, our goal is to model the conditional probabilities of trend growth shifting up or down at time t, given that the last trend shift (or the beginning of the sample) happened d years ago :

$$\Pr(T_j = t, \Delta\tau(T_j) > 0 | T_j - T_{j-1} \geq d, \mathbf{x}_{t-1}) \tag{4.3}$$

$$\Pr(T_j = t, \Delta\tau(T_j) < 0 | T_j - T_{j-1} \geq d, \mathbf{x}_{t-1}) \tag{4.4}$$

as functions of the competing forces $\mathbf{x}_{t-1}$.

Without the conditioning on $\mathbf{x}_{t-1}$, equations 4.3 and 4.4 are nothing else than the up and down-shift hazard rates $\alpha^U(d)$ and $\alpha^D(d)$, i.e. equations 3.3 and 3.4, rewritten in calendar time t instead of duration time d by noting that $d = t - T_{j-1}$ and $D_j = T_j - T_{j-1}$.

This arises because we think of trend shifts as recurrent events and adopt what in the survival literature is sometimes called a "reset-clock" approach. After each trend shift, we reset the clock to zero, and once the minimum trend growth duration has elapsed, the country becomes once again "at risk" of experiencing yet another trend shift.

An important assumption underlying "reset-clock" specifications is that "the processes affecting the occurrence of the first event are the same as those for the second, third, and later events" (Allison [6]). In our case, however, trying to disentangle the competing forces that have systematically been important determinants of trend growth durations and shifts is precisely the goal, hence this assumption seems fully appropriate.

A potentially more important limitation of a "reset-clock" specification is the assumption that the hazards do not depend on all the event history, i.e. only on when the last trend shift happened but not when the previous shifts had happened. However, this assumption can be easily relaxed by introducing explanatory variables that represent the dependency of the hazard on the country's previous history (Allison [6]), which is what we do by including among our covariates variables like the trend growth rate and growth volatility, estimated on rolling samples, i.e. from the beginning of the sample up to and including time $t-1$, thereby taking into account all the previous growth history of the country.

Another issue in models with repeatable events is the intra-subject correlation arising from having multiple observations (and potentially also multiple events) per country. In what follows, we adopt a so-called "marginal approach" (cf. Grambsch and Therneau [21] (chapter 8)), which does not include country random or fixed effects, but corrects the standard variance estimates for intra-country correlations. Different approaches could be explored in future work.

In reality, we have already started investigating the determinants of trend growth durations in the previous section where we examined how survivor functions change depending on whether the country is a developing or a developed economy. Since we were only interested in the effect of one specific characteristic - an indicator for being a developing economy, we could proceed in a simple, intuitive way: divide our sample into developed and developing countries, construct the survivor functions non-parametrically as explained in footnote 8, plot the results and inspect them visually.

Unfortunately, this simple approach does not work if our goal is to examine the simultaneous effects of several discrete and continuous characteristics on the hazards. Moreover, it does not give us one quantitative statistic that summarizes the effect of a characteristic and which would allow us to gauge its statistical and economic significance, and to compare it to the effects of other characteristics.

A simple way around these issues, is to assume a specific functional form that relates the hazards to the characteristics $\mathbf{x}_{t-1}$. Since the discrete-time hazards are conditional probabilities, the functional form needs to be such that the estimated hazards lie between 0 and 1 and the hazards of the three possible outcomes - up-shift, down-shift and no shift - sum to one.

In Cox's [13] original paper, where he proposed the partial likelihood method for the estimation of the proportional hazards model for continuous-time survival analysis, he also suggested that a logit specification could be employed in the discrete case and reduces to a proportional hazards model when the time interval considered gets very small. Later, the model was extended to the competing risks situation by relating the covariates $\mathbf{x}_{t-1}$ to the hazards through a multinomial logit specification (e.g. Allison [6], Allignol et al. [5]):

$$\alpha^S(t) = \frac{\exp(\mathbf{x}_{t-1}'\beta^S)}{1+\sum_{S=U,D}\exp(\mathbf{x}_{t-1}'\beta^S)} \tag{4.5}$$

where, for ease of notation, we write $\alpha^S(t) \coloneqq \alpha^S(t - T_{j-1}|\mathbf{x}_{t-1})$ with $S = U, D$. The parameters β^S capture the cause-specific effects of the covariates on the S outcome relative to no shift.

To see the intuition behind this functional form, suppose a country reaches year t without having yet experienced a novel shift in its trend growth since the last one, and the minimum trend growth duration has elapsed. What can happen in year t? The trend can either shift up, shift down or not shift at all. The problem is therefore akin to a conditional multinomial choice model where the conditional probabilities of the three possible events/choices are:

$$\alpha^U(t), \alpha^D(t) \text{ and } 1 - \alpha(t)$$

Note that equation 4.5 indeed ensures that the estimated conditional probabilities lie between 0 and 1, and sum up to 1, since the conditional probability of no shift (reference category) is:

$$1 - \alpha(t) = \frac{1}{1 + \sum_{S=U,D} \exp(\mathbf{x}'_{t-1}\beta^S)} \tag{4.6}$$

Appendix 6.1 explains in details how the likelihood function in our case should be constructed and therefore how the model parameters can be estimated by maximum likelihood.

To see how the parameters should be interpreted, suppose we have two covariates: x_{1t-1} and x_{2t-1}. The probability of experiencing an up-shift in year t relative to experiencing no-shift in year t, conditional on having experienced no shifts since T_{j-1} is:

$$\frac{\alpha^U(t)}{1 - \alpha(t)} = \exp(\beta_1^U x_{1t-1} + \beta_2^U x_{2t-1}) \tag{4.7}$$

$\exp(\beta_1^U x_{1t-1} + \beta_2^U x_{2t-1})$ is often called the relative risk associated with covariate values x_{1t-1} and x_{2t-1} . More precisely, $\exp(\beta_1^U x_{1t-1} + \beta_2^U x_{2t-1})$ is the risk of an up-shift relative to no shift. Taking logs:

$$\log\left(\frac{\alpha^U(t)}{1 - \alpha(t)}\right) = \beta_1^U x_{1t-1} + \beta_2^U x_{2t-1} \tag{4.8}$$

hence β_1^U measures the change in the multinomial log-odds of an up-shift in trend growth relative to no shift due to a one unit change in x_{1t-1} holding x_{2t-1} fixed.

Another, perhaps more intuitive, interpretation arises from writing:

$$\frac{\exp(\beta_1^U(x_{1t-1}+1)+\beta_2^U x_{2t-1})}{\exp(\beta_1^U x_{1t-1}+\beta_2^U x_{2t-1})} \quad = \quad \exp(\beta_1^U) \tag{4.9}$$

i.e. when x_{1t-1} increases by one unit while x_{2t-1} is fixed, the relative up-shift risk is multiplied by $\exp(\beta_1^U)$. For instance if $\exp(\beta_1^U) = 0.8$, the risk of an up-shift relative to no-shift falls by 20%. A value of 1 means there is no effect on the relative up-shift risk. If $\exp(\beta_1^U) > 1$, the risk rises by $(\exp(\beta_1^U) - 1)$%.

4.2. **Results: time-to-shift determinants.** The economic history examples discussed above point to two types of variables that could be of potential interest:

- some characteristics of the growth, political, institutional, external ... environment which either create favorable (detrimental) conditions for trend up-shifts, or protect the country from (make it more vulnerable to) down-shifts;
- certain shocks which act as catalysts.

There is an important trade-off in selecting variables for such a large heterogeneous set of countries. On the one hand, we want to be able to estimate the model on a relatively large sample so that our results are not driven by a selected few experiences. On the other hand, not including certain variables may lead to an omitted variable bias and affect our coefficient estimates and significance.

In what follows, we examine a large set of covariates which can be regrouped into five dimensions:

(1) *Growth environment:* we investigate the effects of the trend growth rate, the number of years since the last shift, the cyclical component and growth volatility (standard deviation of annual growth rates). All these variables are estimated on rolling samples, i.e. for instance, we only use growth data up to and including t to estimate the trend in year t. Using rolling samples is important because the estimates of trend growth may change as we fit iFF on enlarged samples if different shift dates are identified. Hence, using trend growth estimated on the complete sample would be forward-looking. A similar argument can be advanced for the other three variables. For instance, using a time-invariant estimate of growth volatility based on the whole sample of data introduces a look-ahead bias as it implies that at any point in time we know what would be happening to growth in the future. It is true that using rolling samples, especially when these are relatively small, introduces measurement error and could attenuate our estimated coefficients. However, given our interest in employing this model as a predictive tool, the look-ahead bias issue seems more important.

(2) *Development and Demography:* instead of a discrete classification of countries into "developed" and "developing", we employ a set of variables which capture

both material and non-material aspects of development: the real GDP p.c. in Purchasing Power Parity[9], fertility, infant mortality, life expectancy, the level of urbanisation, primary, secondary and tertiary gross enrollment ratios, the percentage of total population aged less than 14 and the percentage of total population aged 65 and above. We examine these variables both in levels and changes over the past 2 years.

(3) *Institutions and political stability:* we use the POLITY database described in Gurr et al. [22]. In particular, the Polity 2 score, measured on a scale from -10 (strongly autocratic) to +10 (strongly democratic), changes in the Polity 2 score over the past two years, and the durability of the regime's authority (number of years since the last substantive change in authority characteristics defined as a 3-point change in the Polity score, cf. [22]). To capture political stability, we employ the Cross-National Time-Series Data Archive (CNTS). In particular, the Weighted Conflict Index, which is a weighted sum of the number of assassinations, general strikes, guerrilla warfare, government crises, purges, riots, revolutions and anti-government demonstrations from the Domestic Conflict Event Data part of the CNTS. The compilation methods and the construction of the index are explained in Wilson [41]. We look at the level and growth in WCI. The latter is winsorized at 100% and a dummy variable equal to 1 when the WCI increases by 100% or more is included. We also use several variables from the Political Data part of CNTS: the number of Coups d'Etats, Major Constitutional Changes, Major Cabinet Changes, Changes in Effective Executive, and the number of Legislative Elections.

(4) *Economic management*: we consider the annual inflation rate (GDP Deflator), domestic credit to the private sector (% of GDP), gross capital formation (% of GDP), gross domestic savings (% of GDP). We examine these variables both in levels and percentage point changes. Two variables capture trade: exports plus imports (as % of GDP), and the difference between the annual growth rates of imports and exports. We also look at the annual depreciation of the official nominal exchange rate against the US dollar. The variable is winsorized above at 100%, and a dummy tracks winsorized observations. We allow the effect of the depreciation to be different in the case of a fixed exchange rate regime by including a term which interacts the depreciation with a dummy equal to one if the exchange rate is fixed.[10]

[9]Real GDP per capita in PPP is constructed using the PWT (rgdpe/pop) and extended to 2015 with World Bank data. All remaining variables are taken from the World Bank Development Indicators, unless another data source is explicitly specified.

[10]We use the IMF AREAER database for the classification of exchange rate regimes.

(5) *External environment & shocks:* we take the annual average and the annual percentage point change in the daily US T-bill (secondary market, 3 month rate). For commodity prices, we use the IFS monthly gold, food and oil price indices. We consider the annual averages, and the growth rates between January and December. We also interact the annual growth in food/oil prices with a dummy equal to 1 if the country is a food/oil exporter and another dummy equal to 1 if the country is a food/oil importer. The overall impact of the annual growth in food/oil prices in year $t-1$ therefore enters the hazard functions as follows:

$$(\beta + \beta_X \mathrm{I}^X_{t-1} + \beta_M \mathrm{I}^M_{t-1}) x_{t-1}$$

where I^X_{t-1} is a dummy equal to 1 if the food/fuel exports represent at least 20% of merchandise exports in year $t-1$. Similarly, I^M_{t-1} is an indicator function that takes a value of 1 in $t-1$ if food/fuel imports represent at least 20% of merchandise imports in that year.

Given the trade-off between sample size and omitted variable bias, we proceed sequentially, examining one/two additional categories of variables at a time while keeping those that have been previously identified as significant. We fit the models both with and without five-year dummies to check whether the effects estimated are robust to the inclusion of some time-varying unobserved heterogeneity. We do not use a full set of year dummies because it leads to significant over-fitting and non-convergence of the likelihood function, especially in more complex specifications. Moreover, in our exploratory exercise, unlike the predictive model of the following subsection, we shall use the same sets of covariates for both up and down-shift hazards since, a priori, we do not know which covariates enter which hazard function.

Note that all result tables show exponentiated coefficients, i.e. the interpretation is in terms of relative risk ratios, as explained above.

We start with a baseline specification which only includes the *Growth environment* variables: Table 2, models (1) and (2).

The most significant variable in economic and statistical terms is the *Trend growth rate*. Considering the first specification, a one percentage point higher trend growth rate reduces the relative up-shift risk and increases the relative down-shift risk by about 20%. This result illustrates the regression to the mean phenomenon - the idea that an extended period of high growth is rarely sustainable for a long time and more likely to be followed by a period of average rather than even higher growth. Pritchett and Summers [34] have extensively studied this phenomenon in a recent paper, concluding that empirically it is the "most salient feature of economic growth". Our study confirms this finding since trend growth remains the most significant variable throughout the

Table 2: Growth environment, development and demography

	(1)		(2)		(3)		(4)	
	Up	*Down*	*Up*	*Down*	*Up*	*Down*	*Up*	*Down*
Trend growth rate	0.789***	1.201***	0.774***	1.204***	0.763***	1.237***	0.774***	1.243***
	(-9.85)	(7.11)	(-9.90)	(7.93)	(-7.01)	(5.14)	(-6.85)	(6.29)
Years since last shift	0.925***	0.959***	0.927***	0.957***	0.934***	0.959***	0.937***	0.958***
	(-6.40)	(-4.25)	(-5.69)	(-4.08)	(-4.52)	(-3.80)	(-4.34)	(-3.72)
Cycle	0.934***	1.125***	0.932***	1.112***	0.905***	1.156***	0.905***	1.147***
	(-4.11)	(5.81)	(-4.31)	(4.82)	(-4.80)	(5.18)	(-4.66)	(4.75)
Growth Volatility	1.056***	1.042	1.061***	1.040	1.027	1.019	1.026	1.020
	(2.71)	(1.55)	(2.91)	(1.30)	(1.44)	(0.86)	(1.40)	(0.81)
Log(Real GDP p.c. PPP)					0.477***	1.383*	0.473***	1.351*
					(-3.32)	(1.88)	(-3.06)	(1.68)
Fertility (births per woman)					0.883	1.689***	0.940	1.621***
					(-0.70)	(4.04)	(-0.34)	(3.76)
Infant Mortality					0.989	1.002	0.987	1.000
					(-1.38)	(0.22)	(-1.60)	(0.00)
Life Expectancy					0.966	0.974	0.952	0.965
					(-1.04)	(-0.98)	(-1.50)	(-1.27)
Urban Population (% total)					1.001	1.005	1.002	1.006
					(0.06)	(0.75)	(0.16)	(0.93)
Fertility (change)					0.670	1.167	0.719	1.003
					(-1.13)	(0.35)	(-0.86)	(0.01)
Infant Mortality (change)					1.008	1.015	1.017	1.015
					(0.32)	(0.70)	(0.64)	(0.71)
Life Expectancy (change)					1.096	0.993	1.151**	0.960
					(1.54)	(-0.10)	(2.24)	(-0.60)
Urban Population (ppt. change)					0.959	1.046	0.968	1.020
					(-0.67)	(0.85)	(-0.53)	(0.40)
Primary Enrol. (% gross)					0.999	1.008*	1.001	1.007
					(-0.19)	(1.73)	(0.18)	(1.61)
Secondary Enrol. (% gross)					1.003	0.997	1.003	0.998
					(0.44)	(-0.49)	(0.38)	(-0.29)
Tertiary Enrol. (% gross)					1.002	1.007	1.001	1.008
					(0.17)	(0.89)	(0.12)	(0.99)
Primary Enrol. (ppt. change)					0.988	0.994	0.983	0.999
					(-0.86)	(-0.53)	(-1.23)	(-0.10)
Secondary Enrol. (ppt. change)					1.016	1.016	1.014	1.014
					(0.98)	(1.39)	(0.79)	(1.31)
Tertiary Enrol. (ppt. change)					1.057*	1.010	1.038	1.021
					(1.88)	(0.37)	(1.18)	(0.83)
Pop. ages 0-14 (% of total)					0.934*	0.938*	0.917**	0.943*
					(-1.76)	(-1.90)	(-2.17)	(-1.76)
Pop. ages >=65 (% of total)					0.857***	0.971	0.841***	0.965
					(-2.86)	(-0.68)	(-3.10)	(-0.80)
Pop. ages 0-14 (ppt. change)					1.069	1.004	1.042	1.028
					(0.66)	(0.04)	(0.39)	(0.27)
Pop. ages >=65 (ppt. change)					1.497	1.146	1.488	1.235
					(1.25)	(0.55)	(1.24)	(0.84)
Five Year dummies	No		Yes		No		Yes	
Observations	4062		4062		2856		2856	
Pseudo R^2	0.129		0.152		0.180		0.204	

Notes: Exponentiated coefficients; t statistics in parentheses. Standard errors clustered at country level.
Changes taken over past two years. All variables lagged one year.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

analysis. On its own (regression not shown), the trend growth rate explains almost 10% of trend up and down-shifts.

The duration of the current trend growth episode (*Years since last shift*) has a negative impact on both up and down-shift relative risks. Intuitively, if the country has been growing at the same trend growth rate for a longer period of time, it is more likely that this rate corresponds to a long run equilibrium from which the country is less likely to be destabilized. This variable might also be capturing to some extent the level of development since, as shown in Figure 3.5, trend growth durations are longer in developed economies. Indeed, as we introduce variables from our development bucket into the regression, the magnitude of the effect of duration on up-shifts drops from one additional year since the last trend shift reducing the relative up-shift risk by 7.5% (model 1) to decreasing it by 6.6% (model 3).

The effect of the *Cycle* goes in the same direction as that of the trend: decreases the likelihood of up-shifts and increases that of down-shifts. Mechanically, the reason can be explained as follows: the cycle is computed as growth minus the rolling estimate of the trend. Hence, a higher cycle indicates that our rolling estimate of trend growth is going up and that a trend down-shift from this higher estimate is even more likely. Therefore, the cycle accentuates the effect of the trend that we have just discussed.

Higher *Growth volatility* increases both up and down-shift relative risks although the effect is statistically insignificant for down-shifts and becomes also insignificant for up-shifts as development variables are introduced. Economically, the effect goes in the expected direction though - countries with higher growth volatility have shorter trend growth episodes - hence, we decided to keep this variable as a control.

Including five-year dummies in specification (2) does not greatly affect the magnitude and significance of the growth environment variables, suggesting that these variables are robust to some unobserved time-varying heterogeneity.

Models (3) and (4) incorporate *Development and Demography* variables.

A higher level of *Real GDP p.c. in PPP* decreases the likelihood of up-shifts and increases that of down-shifts. This result agrees with our earlier discussion of economic convergence at the end of section 3.2: as countries become more developed, growth slows down. Relative to the no shift outcome, countries start experiencing less up-shifts and more down-shifts. The larger and more significant effect on the up-shifts was expected from our previous discussion and the right panel of Figure 3.5. The coefficients are more difficult to interpret this time since we are looking at the log of the real GDP p.c. The unexponentiated coefficients are -0.74 and 0.32; hence a 10% higher real GDP p.c.

this year is associated with a 7% fall in the up-shift relative risk and a 3% rise in the down-shift relative risk next year.[11]

Real GDP p.c. only captures the material aspect of development. For instance, in 2015, Qatar, Singapore, and the United Arab Emirates ranked above the developed country with the highest real GDP p.c. - Norway. Hence, the simple developed/developing divide gets blurred when we think about development in continuous terms. Unfortunately, very few variables reflecting the non-material side of development appear to be significant. This is not surprising given the results from previous studies. For instance, Berg et al. [12] examine the significance of primary and secondary education, adult and child mortality (levels and within growth spell changes) for the duration of growth spells. They only find three out of eight variables to be significant at the 10% level.

A high level of *Fertility* appears to be detrimental to trend growth: one extra child per woman increases the down-shift relative risk by over 60%. Historically, very high fertility rates (7-8 children per woman) characterize several African countries, e.g. Rwanda, Kenya, Oman, Jordan, in the 1970s and 1980s. The damaging effect of fertility could arise because high fertility is often the flipside of a lower level of female education and employment which are detrimental to growth and that we are not controlling for in the regression because this type of data is less common and less reliable.

Higher percentages of *Population aged 0 to 14* or *65 and above* reduce the relative risk of up-shifts, with the effect being bigger and more significant for the 65 and above age bracket. The effect is consistent with larger dependency ratios preventing the savings rate to rise and engender a trend growth up-shift as in a standard AK growth model (Romer [36]). Conditional on fertility, *Population aged 0 to 14* also appears to protect from down-shifts to some extent, perhaps indicating a potential positive effect on trend growth arising from a future younger and larger active labour force.[12]

An argument often put forward for the case that China still has decades left to run at high growth rates before slowing down is that its level of urbanization, which currently stands at 55.6% of the total population, is much lower than that of the USA (81.6%). Given the results in Table 2, we can neither buttress nor reject this argument because none of the variables related to urbanization are significant. However, it seems that the effect of an increase in *Urban population*, although insignificant, goes in the direction of increasing the likelihood of down-shifts while decreasing that of up-shifts.

[11]To see where these numbers come from note that: $\exp(\beta \ln x_1)/\exp(\beta \ln x_2) = \exp(\beta \ln(\frac{x_1}{x_2}))$. Hence, for instance, a 10% higher real GDP p.c. multiplies the up-shift relative risk by $\exp(-0.74 \ln(1.1)) \simeq 0.93$, a 7% decrease.

[12]See Higgins [25] for an investigation of how demography and national savings are related and a discussion of the dependency debate.

A one percentage point increase in the *Tertiary education* gross enrollment ratio over the past two years raises the up-shift relative risk by 5.7% suggesting, as expected, that more higher education is beneficial for trend growth. The small positive effect of *Primary education* on the down-shift relative risk is less intuitive. Both education effects are only significant at the 10% level and not robust to the inclusion of five-year dummies in specification (4). On the other hand, the beneficial effect of an improvement in *Life expectancy*, only appears as significant once time effects are included. This weakness in robustness to the inclusion of other covariates is confirmed in the next set of results, shown in Table 3, where all three variables completely loose significance once we control for the quality of *Institutions, political stability* and *Economic management*.

Acemoglu et al.[1] provide an extensive overview of the various channels through which weaker institutions may disrupt long term growth. In agreement with this, we find that a one unit lower *Polity 2 score* (less democratic institutions) increases the down-shift relative risk by around 5%. Changes in the Polity score are also very important: as expected, a one unit *Amelioration* over the past two years reduces the down-shift relative risk, while a one unit *Deterioration* increases it. Interestingly, the Polity score and changes thereof have no significant effect on the up-shifts, perhaps indicating that good institutions on their own are not enough to substantially lift trend growth. The *Durability of the Polity regime* reduces both up and down-shifts suggesting that political stability leads to growth stability.

Only one out of the six variables from the CNTS database examined happens to be significant: a dummy equal to 1 if the Weighted Conflict Index (WCI) rises by more than 100%. *Conflict rise >=100%* multiplies the relative risk of down-shift by 2. The finding that the remaining political stability variables are insignificant seems a bit surprising. We investigated whether this may be due to the fact that it takes more than one year for the event to have an impact on trend growth by re-fitting the model with the same variables either lagged two years or aggregated over the past two years, however, no more significant effects appeared. We also investigated the components of the WCI separately, but again with no success. Perhaps, this result is at least in part due to the quality of the data. The CNTS derives most of the events used to construct the WCI from the New York Times (cf. Wilson [41]), and it is very likely that many events, especially in the developing world, go unrecorded. It is also worth mentioning, however, that previous studies have also found the effect of conflict not to be robust to the inclusion of other covariates. For instance, Hausmann et al. [24] find that an indicator for war becomes insignificant for the probability of growth collapses when variables like inflation and the change in the Polity score are included in the regression.

Table 3: Institutions, political stability, and economic management

	(5)		(6)		(7)		(8)	
	Up	*Down*	*Up*	*Down*	*Up*	*Down*	*Up*	*Down*
Trend growth rate	0.747***	1.388***	0.756***	1.376***	0.787***	1.372***	0.778***	1.379***
	(-6.72)	(6.58)	(-6.70)	(6.48)	(-6.80)	(7.24)	(-7.38)	(7.28)
Years since last shift	0.947***	0.981	0.951***	0.983	0.939***	0.986	0.943***	0.986
	(-2.91)	(-1.50)	(-2.68)	(-1.30)	(-3.55)	(-1.22)	(-3.18)	(-1.22)
Cycle	0.891***	1.235***	0.887***	1.218***	0.926***	1.208***	0.919***	1.198***
	(-3.59)	(4.47)	(-3.62)	(4.18)	(-2.78)	(5.95)	(-2.96)	(5.35)
Growth Volatility	1.025	0.998	1.025	1.001	1.017	1.012	1.023	1.011
	(1.28)	(-0.10)	(1.26)	(0.03)	(0.85)	(0.79)	(1.11)	(0.70)
Log(Real GDP p.c. PPP)	0.527***	1.560*	0.501***	1.481	0.553***	1.687***	0.527***	1.604**
	(-2.80)	(1.77)	(-3.02)	(1.47)	(-3.78)	(2.79)	(-3.84)	(2.44)
Fertility (births per woman)	0.710	1.873***	0.777	1.749**	0.801	1.380**	0.762*	1.406*
	(-1.62)	(2.83)	(-1.16)	(2.36)	(-1.48)	(2.03)	(-1.65)	(1.81)
Pop. ages 0-14 (% total)	0.956	0.952	0.923**	0.957	0.944**	0.997	0.941*	0.994
	(-1.17)	(-0.89)	(-1.99)	(-0.76)	(-2.05)	(-0.07)	(-1.93)	(-0.12)
Pop. ages >=65 (% total)	0.939	1.022	0.898*	1.026	0.932*	1.058	0.913*	1.066
	(-1.09)	(0.30)	(-1.74)	(0.32)	(-1.67)	(0.99)	(-1.95)	(1.05)
Primary Enrol. (% gross)	0.997	1.008	0.997	1.007				
	(-0.44)	(1.41)	(-0.38)	(1.16)				
Tertiary Enrol. (ppt. change)	1.047	1.025	1.027	1.043				
	(1.18)	(1.03)	(0.62)	(1.61)				
Life Expectancy (change)	1.088	0.982	1.105	0.973				
	(1.00)	(-0.28)	(1.14)	(-0.41)				
Polity 2 score (level)	0.993	0.955**	0.999	0.953**	0.973	0.947***	0.976	0.948***
	(-0.30)	(-2.27)	(-0.04)	(-2.27)	(-1.48)	(-3.24)	(-1.26)	(-2.85)
Amelioration Polity 2	1.007	0.667***	0.995	0.677***	0.980	0.858***	0.984	0.872**
	(0.17)	(-3.12)	(-0.12)	(-3.04)	(-0.52)	(-2.69)	(-0.42)	(-2.25)
Deterioration Polity 2	0.933	1.147**	0.911	1.164**	0.997	1.157***	0.988	1.151**
	(-1.15)	(2.19)	(-1.48)	(2.22)	(-0.07)	(2.60)	(-0.28)	(2.53)
Durability Polity regime	0.983***	0.982***	0.982***	0.981***	0.977***	0.980***	0.977***	0.980***
	(-2.92)	(-3.69)	(-2.99)	(-3.67)	(-3.62)	(-4.05)	(-3.56)	(-3.98)
Coups d'Etats	0.433	2.177	0.415	2.572				
	(-0.76)	(0.88)	(-0.81)	(1.06)				
Major Constitutional Changes	0.853	1.660	0.910	1.529				
	(-0.39)	(1.25)	(-0.22)	(1.02)				
Changes in Effective Executive	1.048	0.963	1.076	0.946				
	(0.18)	(-0.10)	(0.28)	(-0.15)				
Legislative Election	0.998	0.836	0.998	0.856				
	(-0.01)	(-0.68)	(-0.01)	(-0.57)				
Weighted Conflict Index (WCI)	1.000	1.000	1.000	1.000				
	(0.25)	(-0.61)	(0.69)	(-0.73)				
WCI growth, win.	1.001	1.001	1.000	1.001				
	(0.69)	(0.43)	(0.20)	(0.74)				
Conflict rise >=100%	0.931	2.420***	0.992	2.260**	0.874	1.963**	0.867	1.942**
	(-0.18)	(2.70)	(-0.02)	(2.39)	(-0.43)	(2.39)	(-0.44)	(2.33)
Log(1+inflation)	1.441	3.959***	1.392	3.123**	1.259	3.011***	1.235	2.558**
	(0.82)	(2.71)	(0.79)	(2.39)	(0.60)	(2.70)	(0.56)	(2.48)
Capital formation (gross, % GDP)	0.983	0.991	0.982	0.995				
	(-1.31)	(-0.66)	(-1.27)	(-0.35)				
Capital formation (ppt. change)	0.996	0.995	0.999	0.994				
	(-0.13)	(-0.16)	(-0.05)	(-0.19)				
Domestic savings (gross, % of GDP)	1.002	1.004	1.004	1.003				
	(0.30)	(0.48)	(0.56)	(0.36)				
Domestic savings (ppt. change)	1.038*	0.958*	1.038*	0.970	1.022	0.959***	1.024	0.970**
	(1.96)	(-1.76)	(1.91)	(-1.21)	(1.28)	(-2.92)	(1.24)	(-2.02)

	(5)		(6)		(7)		(8)	
	Up	*Down*	*Up*	*Down*	*Up*	*Down*	*Up*	*Down*
Domestic credit to private (% GDP)	0.997	1.004	0.996	1.003				
	(-0.59)	(1.12)	(-0.68)	(0.87)				
Domestic credit to private (ppt. change)	0.996	1.026***	0.996	1.030***	0.996	1.033***	0.998	1.036***
	(-0.33)	(2.78)	(-0.30)	(2.61)	(-0.37)	(3.81)	(-0.19)	(3.55)
Depreciation (LCU/$), win.	1.015**	0.976*	1.014**	0.983	1.014***	0.987	1.013***	0.991
	(2.56)	(-1.78)	(2.39)	(-1.35)	(3.06)	(-1.58)	(2.85)	(-1.13)
Depreciation x Fixed Exchange	0.998	1.019	1.000	1.015				
	(-0.23)	(1.28)	(-0.06)	(1.04)				
Depreciation >=100%	0.0673***	0.443	0.0802***	0.446	0.156***	0.405	0.182**	0.402
	(-2.88)	(-0.51)	(-2.87)	(-0.56)	(-2.61)	(-0.60)	(-2.48)	(-0.71)
Imports gr. - Exports gr.	1.004	1.018**	1.006	1.017**	0.999	1.016***	1.001	1.016***
	(0.50)	(2.52)	(0.73)	(2.46)	(-0.22)	(2.90)	(0.08)	(2.99)
Trade (% of GDP)	1.010***	1.001	1.012***	1.001	1.003*	1.000	1.004**	1.000
	(2.98)	(0.44)	(3.38)	(0.38)	(1.86)	(0.21)	(2.44)	(0.29)
Five Year dummies	No		Yes		No		Yes	
Observations	2194		2194		2625		2625	
Pseudo R^2	0.243		0.264		0.213		0.237	

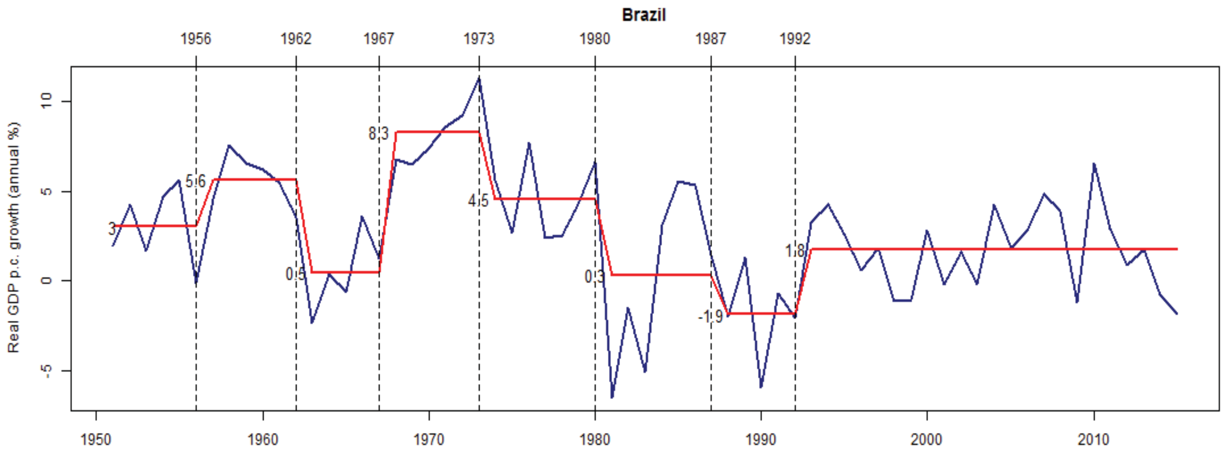
Exponentiated coefficients; t statistics in parentheses. Standard errors clustered at country level. All variables lagged one year.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

We examine several aspects of *Economic management* starting with monetary stability as measured by the log of 1 plus the annual *Inflation* rate, a standard transformation in the empirical growth literature. Higher inflation significantly increases the likelihood of down-shifts. This result is not surprising; many examples in economic history indicate that inflation is a symptom of economic mismanagement. For instance, all four trend growth down-shifts in Brazil, illustrated in Figure 4.1, were preceded by very high inflation rates: 31% in 1961, 19% in 1972, 56% in 1979 and 145% in 1986, while the success of the *"Plano Real"* (1994-2002), which managed to stabilize the Brazilian economy at the current trend growth rate of 1.8% p.a. since 1993, relied to a large extent on having achieved monetary stability through measures like a peg of the Brazilian real to the US dollar and a general indexation of prices (e.g. cf. Feijo et al. [17]).

Another important determinant of macroeconomic stability is the exchange rate. We look at the *Depreciation* of the official nominal exchange rate against the US dollar. The coefficient estimates indicate that a one percentage point larger *Depreciation* raises the up-shift relative risk by about 1.5%, and this effect does not disappear if the exchange rate is fixed. One particular channel through which a devaluation this year can boost growth next year is by making the country's exports more competitive. However, the dummy indicator for a devaluation of 100% and more (*Depreciation>=100%*) almost completely annihilates the up-shift relative risk.

Just as human capital accumulation, physical *Capital formation* does not seem to be a significant predictor of trend growth dynamics. This agrees with two studies

Figure 4.1 Trend growth in Brazil (1951-2015)



Notes: Trend growth (red) extracted from annual real GDP p.c. growth data (blue) using iFF.

that employ growth accounting techniques (parametric in Jones and Olken [28], non-parametric in Kerekes [30]) to investigate the sources of important growth changes and conclude that factor accumulation only plays a negligible role in them so that "even medium-run growth rate changes are mainly the result of productivity changes"[30].

Two other variables that matter for trend shifts are domestic indebtedness and savings. Both variables are significant in percentage point changes but not in levels. The positive effect of a rise in *Domestic savings* on up-shifts disappears as other insignificant covariates are dropped from the up-shift hazard function, cf. specifications (7) and (8). However, the protective effect from down-shifts remains significant: a one ppt. increase in domestic savings this year reduces the relative down-shift risk next year by around 3%. In developing economies, higher internal savings may help avoid the dramatic economic disruptions caused by sudden outflows of foreign investment. In developed economies, increases in domestic savings can help finance innovation and therefore prevent growth from shifting down.

Increases in domestic indebtedness played a prominent role in the most recent down-shifts. However, as the following table suggests, the lesson that a rise in *Domestic credit to the private sector* may not be good for trend growth could perhaps have been assimilated already after the Latin American turmoil in the 1980s and the Asian crisis of the 1990s.

Country	Down-shift	Rise in domestic credit to private sector in preceding year (ppt. of GDP)
Spain	2007	20.6
Ireland	2007	19.7
Cyprus	2008	18.0
Malaysia	1997	17.2
Thailand	1996	13.1
Chile	1981	10.6

We also find that while a higher proportion of GDP in *Trade* is prospicious to trend growth up-shifts, a rising trade deficit (*Imports growth - Exports growth)* is a symptom of future trend down-shifts.

The remaining specifications in Table 3 show that adding five-year dummies and dropping insignificant covariates does not qualitatively alter the effects just identified in most cases, even though the precise quantitative estimates may change.

Table 4 keeps the variables previously identified as significant and adds the last category: *External environment & shocks*.

The *US T-bill rate* is considered as the risk-free rate on the market and is therefore an important determinant of borrowing costs. Model (9) indicates that both high US rates and rises thereof are bad for trend growth. For instance, a one percentage point higher US T-bill rate is associated with an 8.5% higher relative down-shift risk and an 8.2% lower relative up-shift risk. Interestingly, as we include five year dummies in specification (10), the significance of the US T-bill rate drops. The only effect that remains significant is that of the average US T-bill rate on the relative down-shift risk, which is now much bigger: 17% instead of the previous 8.5%. Although US rate hikes are not significant for trend shifts once we control for unobserved time-varying heterogeneity, their significance in the absence of such controls indicates that they may be a good proxy for a part of this unobserved heterogeneity which is detrimental for long-run growth, in particular for up-shifts.

Gold is considered as a safe asset and a hedge in turbulent times. Hence, high gold prices are an indication of high risk aversion. More risk averse investors will only lend money at higher rates thereby potentially raising the costs of financing growth-enhancing projects thereby hurting trend growth. Our analysis indicates that although growth in gold prices is insignificant, high averages decrease the relative up-shift risk and increase the relative down-shift risk, with the latter effect being robust to the inclusion of five-year dummies.

Table 4: External environment & shocks

	(9)		(10)		(11)		(12)	
	Up	*Down*	*Up*	*Down*	*Up*	*Down*	*Up*	*Down*
Trend growth rate	0.757***	1.368***	0.759***	1.379***	0.761***	1.368***	0.765***	1.374***
	(-7.61)	(6.96)	(-7.74)	(6.68)	(-7.43)	(6.85)	(-7.49)	(6.64)
Years since last shift	0.942***	0.983	0.944***	0.984	0.942***	0.983	0.943***	0.985
	(-3.21)	(-1.41)	(-3.06)	(-1.29)	(-3.29)	(-1.41)	(-3.11)	(-1.27)
Cycle	0.923***	1.173***	0.926**	1.181***	0.921***	1.173***	0.926**	1.178***
	(-2.65)	(4.41)	(-2.47)	(4.24)	(-2.77)	(4.35)	(-2.51)	(4.25)
Growth Volatility	1.031	1.011	1.031	1.012	1.029	1.011	1.028	1.012
	(1.39)	(0.74)	(1.45)	(0.77)	(1.34)	(0.72)	(1.34)	(0.75)
Log(Real GDP p.c. PPP)	0.536***	1.630**	0.509***	1.480**	0.546***	1.645***	0.514***	1.494**
	(-3.60)	(2.52)	(-3.62)	(2.07)	(-3.45)	(2.58)	(-3.48)	(2.09)
Fertility (births per woman)	0.733*	1.416*	0.698**	1.404*	0.740*	1.407*	0.702*	1.390*
	(-1.79)	(1.91)	(-1.96)	(1.69)	(-1.75)	(1.88)	(-1.93)	(1.66)
Pop. ages 0-14 (% total)	0.944*	1.002	0.951	0.995	0.948*	1.003	0.952	0.996
	(-1.81)	(0.05)	(-1.45)	(-0.11)	(-1.71)	(0.06)	(-1.43)	(-0.09)
Pop. ages >=65 (% total)	0.917*	1.061	0.926	1.070	0.920*	1.060	0.923	1.071
	(-1.72)	(0.95)	(-1.44)	(1.04)	(-1.67)	(0.95)	(-1.48)	(1.06)
Polity 2 score (level)	0.978	0.948***	0.981	0.945***	0.979	0.947***	0.980	0.945***
	(-1.07)	(-2.83)	(-0.94)	(-2.71)	(-1.07)	(-2.87)	(-0.98)	(-2.73)
Amelioration Polity 2	0.989	0.780**	0.990	0.784**	0.987	0.778**	0.990	0.782**
	(-0.28)	(-2.06)	(-0.25)	(-2.15)	(-0.32)	(-2.05)	(-0.26)	(-2.12)
Deterioration Polity 2	1.008	1.190**	0.994	1.206**	1.004	1.191**	0.991	1.206**
	(0.18)	(2.39)	(-0.12)	(2.38)	(0.09)	(2.43)	(-0.20)	(2.40)
Duration regime	0.977***	0.979***	0.977***	0.979***	0.978***	0.979***	0.977***	0.979***
	(-3.48)	(-3.73)	(-3.50)	(-3.70)	(-3.44)	(-3.81)	(-3.47)	(-3.79)
Conflict rise >=100%	0.907	2.396***	0.884	2.208***	0.926	2.373***	0.898	2.212***
	(-0.28)	(3.05)	(-0.34)	(2.67)	(-0.22)	(3.02)	(-0.30)	(2.69)
Log(1+inflation)	1.297	1.993*	1.285	2.019*	1.312	2.067*	1.326	2.024*
	(0.68)	(1.77)	(0.67)	(1.79)	(0.72)	(1.89)	(0.76)	(1.81)
Domestic savings (ppt. change)	1.043**	0.947***	1.047**	0.956***	1.043**	0.947***	1.048***	0.957***
	(2.41)	(-3.73)	(2.57)	(-2.85)	(2.37)	(-3.77)	(2.61)	(-2.79)
Domestic credit to private (ppt. change)	1.001	1.034***	1.001	1.036***	1.000	1.033***	0.999	1.035***
	(0.11)	(3.29)	(0.10)	(2.81)	(-0.05)	(3.27)	(-0.09)	(2.77)
Depreciation (LCU/$), win.	1.011**	0.994	1.012**	0.995	1.011**	0.994	1.011**	0.995
	(2.26)	(-0.75)	(2.35)	(-0.71)	(2.25)	(-0.77)	(2.19)	(-0.65)
Depreciation >=100%	0.183**	0.382	0.185**	0.428	0.181**	0.341	0.184**	0.423
	(-2.34)	(-0.89)	(-2.31)	(-0.81)	(-2.31)	(-0.99)	(-2.26)	(-0.79)
Imports gr. - Exports gr.	0.998	1.013**	0.999	1.013**	0.998	1.013**	1.000	1.012**
	(-0.38)	(2.24)	(-0.20)	(2.08)	(-0.29)	(2.21)	(-0.07)	(2.06)
Trade (% of GDP)	1.004**	1.000	1.004**	1.001	1.004**	1.000	1.004**	1.001
	(2.09)	(0.10)	(2.29)	(0.31)	(2.07)	(0.10)	(2.32)	(0.34)
US T-bill (annual change, ppt.)	0.890*	1.089	0.977	1.103	0.873**	1.089	0.928	1.098
	(-1.83)	(1.55)	(-0.30)	(1.59)	(-2.07)	(1.59)	(-0.99)	(1.59)
US T-bill (annual average)	0.918*	1.085***	0.912	1.170*	0.928*	1.092***	0.900*	1.146*
	(-1.86)	(2.60)	(-1.37)	(1.74)	(-1.67)	(2.83)	(-1.70)	(1.77)
Gold price index (annual growth)	0.991	0.997	0.996	1.000				
	(-1.09)	(-0.50)	(-0.43)	(-0.00)				
Gold price index (annual average)	0.976***	1.018***	1.004	1.043***	0.976***	1.020***	1.005	1.039***
	(-3.02)	(3.30)	(0.19)	(3.60)	(-3.09)	(3.57)	(0.29)	(3.78)
Food price index (annual growth)	1.012	1.044***	0.996	1.032**	0.999	1.040***	0.989	1.035***
	(0.77)	(4.10)	(-0.23)	(2.42)	(-0.08)	(4.83)	(-0.82)	(3.46)
Food(growth) x Exporter	1.007	0.968***	1.010	0.969***	1.007	0.968***	1.010	0.969***
	(0.44)	(-2.66)	(0.55)	(-2.65)	(0.44)	(-2.69)	(0.57)	(-2.68)
Food(growth) x Importer	0.993	0.984	0.992	0.984				
	(-0.41)	(-0.82)	(-0.42)	(-0.87)				

	(9)		(10)		(11)		(12)	
	Up	*Down*	*Up*	*Down*	*Up*	*Down*	*Up*	*Down*
Oil price index (annual growth)	0.996	1.000	0.994	1.003				
	(-0.91)	(-0.05)	(-1.38)	(0.70)				
Oil(growth) x Exporter	0.995	0.991**	0.995	0.992*	0.992	0.991**	0.992	0.994
	(-0.69)	(-2.12)	(-0.69)	(-1.86)	(-1.24)	(-2.31)	(-1.32)	(-1.42)
Oil(growth) x Importer	0.995	1.006	0.996	1.006				
	(-0.59)	(1.23)	(-0.48)	(1.22)				
Five Year dummies	No		Yes		No		Yes	
Observations	2464		2464		2464		2464	
Pseudo R^2	0.241		0.259		0.238		0.255	

Exponentiated coefficients; t statistics in parentheses. Standard errors clustered at country level.
All variables lagged one year.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Annual averages of gold, food and oil prices are highly correlated: 0.9 correlation between gold and food, 0.94 correlation between gold and oil. In order to avoid multicollinearity issues, we therefore decided to only focus on food and oil price growth rates and allow the effects to be different for respective exporters and importers.

Rising *Food prices* may increase global food insecurity and poverty, especially in developing countries (cf. e.g. Azzarri et al. [7]), thereby being detrimental to trend growth. Indeed, we find that a one percentage point higher annual growth rate in food prices raises the down-shift relative risk by about 4.4%. This detrimental effect, however, is reversed if the country is a food exporter. In Table 4, the only significant effect of rising *Oil prices* is to slightly protect oil exporting countries from down-shifts.

In further regressions, not shown here but available on request, we investigated several other variables that often appear in the empirical growth literature while keeping the ones that we had already found as significant. The reason for not including these variables in the main specifications presented above is that they reduce the sample size dramatically thereby making results incomparable across specifications, while at the same time often being insignificant.

For instance, we found terms of trade growth to be insignificant while shrinking the sample size from 2464 to 1625. Foreign direct investment net inflows and outflows as a % of GDP are once again insignificant both in levels and ppt. changes, but reduce the sample size to 1768. We investigated the importance of the sectoral composition of the economy by including five variables: the annual growth rates in the value added by the agricultural, manufacturing, and services sectors, and the values added as a % of GDP of the manufacturing and services sectors. The sample size dropped to 1802 and the only effect significant at 10% and robust to the inclusion of five year dummies was that of the growth in the services sector on down-shifts: a one ppt. higher service sector growth increased the relative down-shift risk by about 3.6-3.8%.

Finally, we also looked at short term debt as a percentage of total external debt, finding that a one percentage point higher level increases the down-shift relative risk by almost 5%. The effect is significant at the 0.1% level, and robust to the inclusion of five year dummies. However, unfortunately, including this variable shrinks the sample size from 2464 observations to 1391, mainly because the World Bank provides data on short term debt only for developing countries.

4.3. **Assessing trend growth prospects.** We now wish to turn the insights gained in the previous section about what makes trend growth episodes more or less likely to end next year with an up or a down-shift into a predictive tool that can be used to answer our second motivating question - *"How likely is trend growth to change and in what direction?"* - in real time.

Ideally, we would like to employ all the variables identified as significant in the previous section to give estimates of the conditional probabilities of up and down-shifts in 2016 for most of the countries in our sample. Unfortunately, because of a large number of missing values in 2015, this is not possible. For instance, at the time of writing this paper, the World Bank had updated fertility data for only one country. More annoyingly, some important countries like China and India missed data on either domestic savings or trade.

Although we hope that future research will employ the trend-shifting framework developed in this paper on better datasets and build more interesting and comprehensive predictive models, in what follows, we adopt a less ambitious approach in terms of variables included, but which nevertheless allows us to compare our 2016 hazard estimates for 120 out of the 153 countries for which we have extracted trend growth using iFF.

The up and down-shift hazard estimates reported in Table 7 in the Appendix are constructed using the model shown in Table 5. To get to this model, we re-estimated specification (9) without fertility, domestic savings and the trade variables, then dropped all insignificant effects. Amelioration in Polity 2 score, inflation and growth in oil prices for oil exporters became insignificant, while growth volatility now significantly increases both up and down-shift risks, and a one percentage point higher growth in oil prices decreases the relative up-shift risks around the world by 0.4%. All the other effects go in the same direction as before except for the effect of Pop. ages 0-14 (% total) on down-shifts. A one percentage point larger population in the 0-14 ages bracket now increases the relative down-shift risk by about 7.7%. Note that the protective relationship found in specifications (3) and (4) already became insignificant as we introduced further controls in specifications (5) to (12). However, here the effect goes significantly in the other direction because we are no longer controlling for fertility. Unsurprisingly,

Table 5: Predictive model

	Up	*Down*
Trend growth rate	0.777***	1.271***
	(-8.22)	(6.41)
Years since last shift	0.933***	0.968***
	(-4.22)	(-2.67)
Cycle	0.932**	1.165***
	(-2.56)	(5.87)
Growth Volatility	1.047**	1.025*
	(2.04)	(1.68)
Log(Real GDP p.c. PPP)	0.633***	1.610***
	(-3.51)	(3.67)
Pop. ages 0-14 (% total)	0.913***	1.077***
	(-3.64)	(3.17)
Pop. ages >=65 (% total)	0.897**	1.108***
	(-2.43)	(2.77)
Polity 2 score (level)		0.942***
		(-4.33)
Deterioration Polity 2		1.132*
		(1.75)
Duration Polity regime	0.987***	0.988***
	(-3.07)	(-2.64)
Conflict rise >=100%		2.047***
		(2.65)
Domestic credit to private (ppt. change)		1.038***
		(4.31)
Depreciation (LCU/$), win.	1.010**	
	(2.51)	
Depreciation >=100%	0.349**	
	(-2.08)	
US T-bill (annual average)	0.938*	1.068**
	(-1.79)	(2.47)
US T-bill (annual change)	0.903*	1.114**
	(-1.89)	(2.38)
Gold price (annual average)	0.984***	1.019***
	(-2.97)	(4.05)
Food price (annual growth)		1.035***
		(4.80)
Food price (growth) x Exporter		0.977**
		(-2.21)
Oil price (annual growth)	0.996*	
	(-1.65)	
Observations	3017	
Pseudo R^2	0.197	

Exponentiated coefficients; t statistics in parentheses.
Std. errors clustered at the country level. All variables lagged one year.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Estimated up and down-shift hazards, summary statistics

	Up-shift Hazard	*Down-shift Hazard*
Correlation with Up-shifts	0.188	-0.071
Correlation with Down-shifts	-0.075	0.206
Mean during Up-shifts	0.177	0.043
Median during Up-shifts	0.134	0.022
Mean during Down-shifts	0.035	0.236
Median during Down-shifts	0.018	0.133
Standard deviation	0.107	0.137

the two variables have a correlation of 0.91. Hence, once fertility is excluded Pop. ages 0-14 starts capturing its negative effect discussed above.

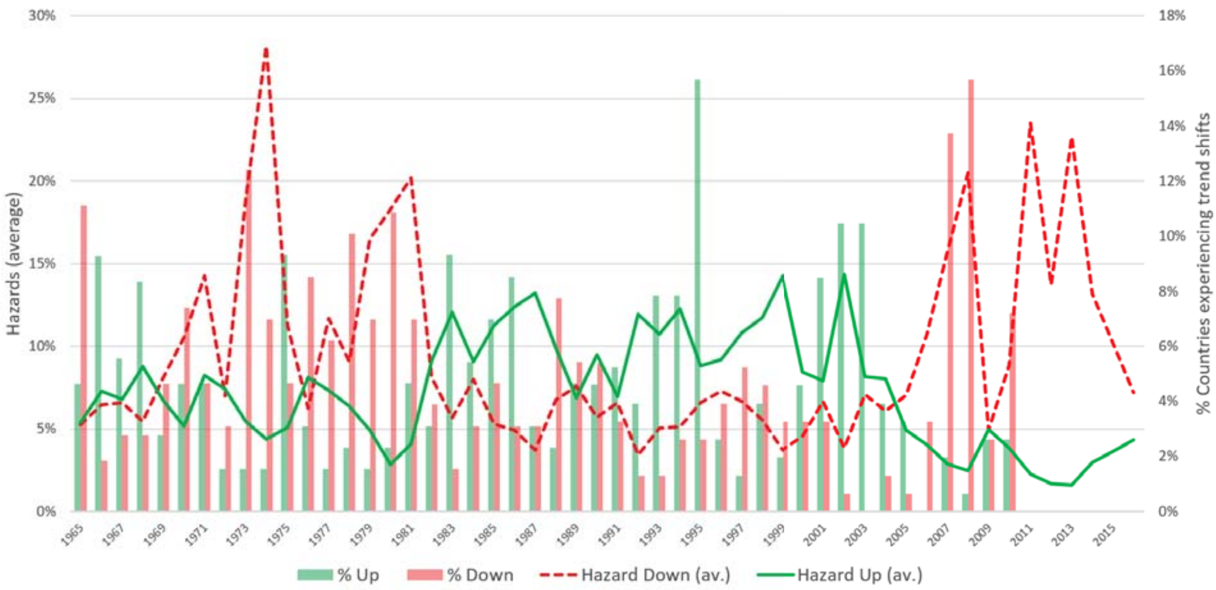
Also note that we are not including five-year dummies. The reason is that in this section, unlike the previous one where we were interested in establishing the robustness of our variables to some unobserved time-varying heterogeneity, what we are really looking for is to find a certain combination of *observable* domestic and external variables which, taken together, have historically been significant predictors of up and down-shifts and that we have previously identified as being robust to such unobserved time effects. We could interpret our exercise as wanting to create indices of trend growth instability based on a certain combination of observable domestic and external variables. Unobserved time effects are not something that we can measure in real time and that could help us predict when the current trend growth episodes will end.

The parsimonious predictive model explains almost 20% of trend shifts, which compares well with the more complex specifications we had before and is quite high given the unpredictable nature of such events. It is better at predicting down-shifts than up-shifts since, as shown in Table 6, the estimated up-shift hazards have a 0.188 correlation with the up-shifts, while the correlation between down-shifts and the estimated down-shift hazards is higher: 0.206.[13] This is not surprising since the up-shift hazard is modelled as a function of 14 variables, whereas the down-shift hazard reacts to 17 variables.

The mean up-shift hazard is over four times higher during up-shifts than during down-shifts (0.177 vs 0.043) and the ratio is around 6 when looking at the median. A more pronounced result holds for down-shifts (6.7 for the mean and 7.4 for the median). However, the mean and median hazard estimates remain quite low, suggesting both that

[13]These correlations are based on the whole sample of 5384 observations for which we can compute the hazards and not only the 3017 observations used to estimate the model.

Figure 4.2 Actual trend shifts & estimated hazards



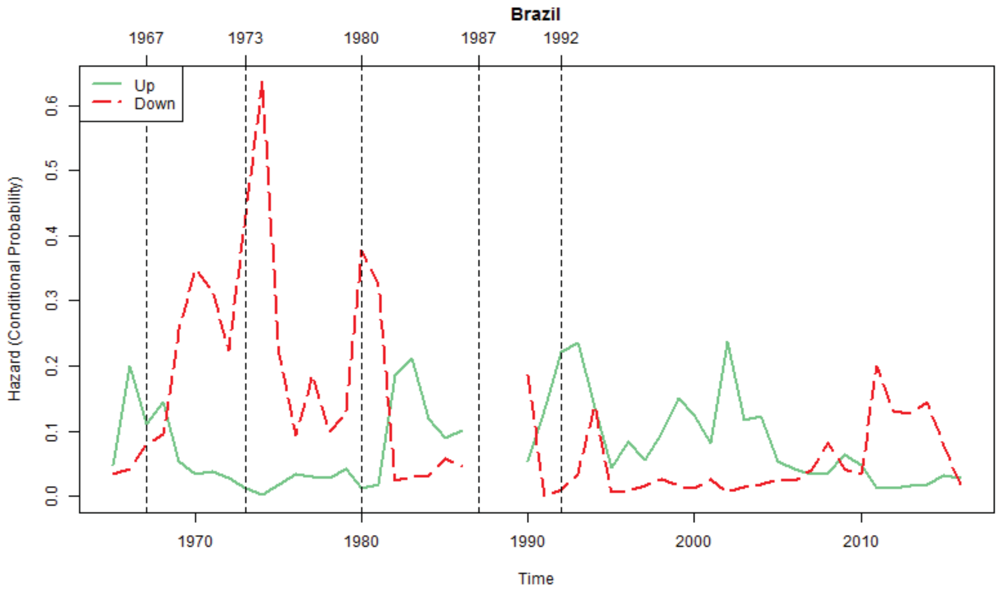
trend shifts are very hard to foretell, and that the model could be improved upon in order to achieve more accurate predictions of trend growth dynamics.

Another interesting way to gauge the performance of the model is to compare the average up and down-shift hazards estimated with the temporal distribution of trend up and down-shifts, analysed in section 3. Figure 4.2 superposes the average up and down-shift hazards estimated for each year with the percentage of countries experiencing up and down-shifts in that year. As we can see, the average hazards seem to follow the pattern of the percentages of the respective trend shifts fairly well. In particular, the average down-shift hazard often dominates the average up-shift hazard at the same times as the percentage of down-shifts is larger than the percentage of trend up-shifts and vice versa. More precisely, the correlations (1965 - 2010) between the average hazards and the percentages of countries experiencing shifts are:

	% Countries experiencing	
Average Hazard	*Up -Shifts*	*Down-Shifts*
Up	0.378	-0.579
Down	-0.383	0.629

It is interesting that although the average up-shift hazard is worse at describing the pattern of when up-shifts happen than the down-shift hazard is for the down-shifts: 0.378 correlation vs. 0.629; the up-shift hazard is more sensitive to when down-shifts happen (-0.579 correlation) than is the down-shift hazard for when up-shifts happen (-0.383 correlation).

Figure 4.3 Estimated hazards for Brazil



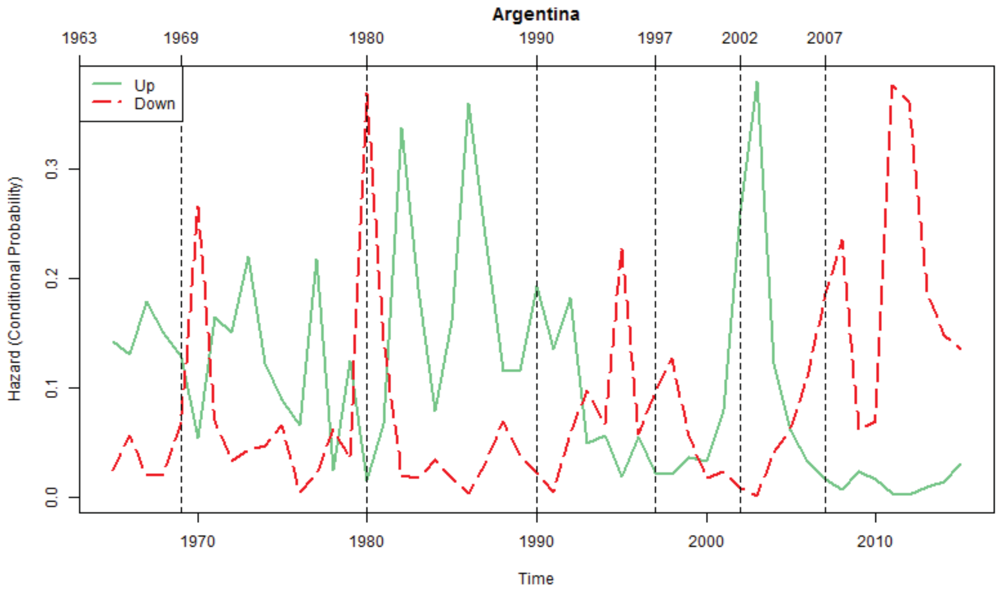
Note: Domestic credit to private sector data missing between 1986 and 1988.

Note that because we assume a minimum trend growth duration of 5 years when extracting trend growth using iFF, we do not find any trend shifts after 2010. Moreover, all the hazard estimates since 2010 are out-of-sample by construction because none of the observations after 2010 are used in the estimation. The evolution of these out-of-sample hazard estimates suggests that many countries might have experienced down-shifts in this period.

One such country is perhaps Brazil. According to Serrano and Summa [37], Brazil has been living through a challenging period since 2011. Figure 4.3 plots the evolution of the estimated hazards for Brazil, showing that there is indeed a spike in the down-shift hazard in 2011. Table 7 tells us that Brazil has been growing at a trend growth rate of 1.76% p.c. p.a. since 1993 (last trend shift in 1992). Taking this into account, the conditional probabilities of Brazilian trend growth shifting either up or down from this 1.76% trend in 2016 are quite low: 2.8% and 1.6%. A shift in trend growth is a shift in the average growth rate for at least the next five years. These probabilities therefore tell us that it is not very likely that the average Brazilian trend growth over at least the next five years will be very different from 1.76% p.a.

Back in 2011, the rolling estimate of Brazilian trend growth computed using iFF on growth time series up to and including 2010 was 3.29%. As shown in Figure 4.3, in 2011, we would have said that there was a 20% probability that Brazil would grow at a trend growth rate that is at least 3 percentage points lower than this 3.29% trend rate over the five years following 2011, i.e. an average growth rate of close to 0% or below

Figure 4.4 Estimated hazards for Argentina



for the years 2012 to at least 2016.[14] Today, in 2016, using data up to and including 2015, we estimate at 1.6% the probability of the event that Brazil experiences a trend down-shift of at least 3 percentage points from its current estimate of trend growth at 1.76%, i.e. grows at a rate of -1.24% p.a. or below between 2017 and at least 2021.

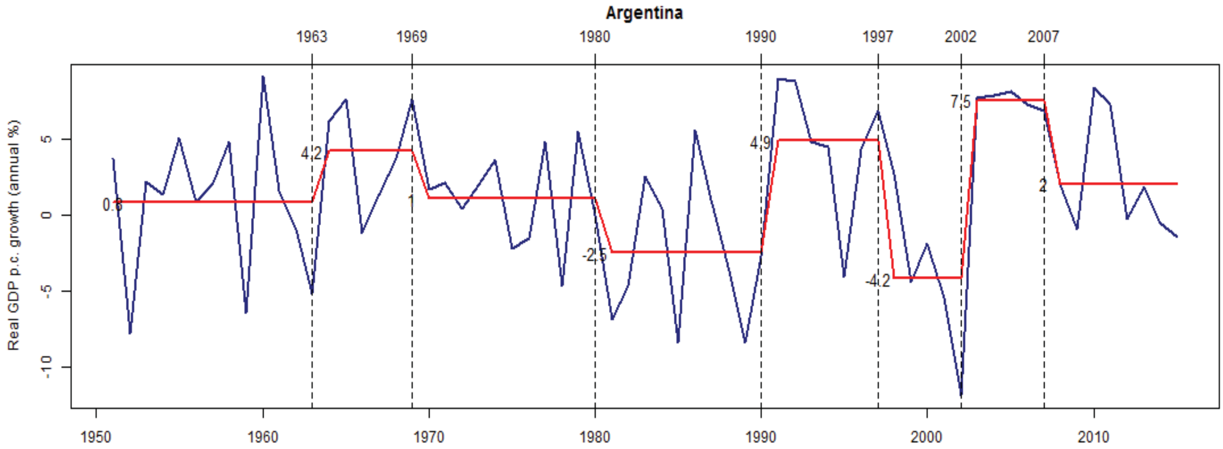
Inspecting the evolution of the hazards visually in Figure 4.3, it seems that down (up) shifts often coincide with spikes in down (up) shift hazards around the shift date, or at least an important rise in the down (up) shift hazard and a fall in the up (down) shift hazard. For instance, for Brazil, 1967 and 1992 are up-shifts, while 1973 and 1980 are down-shifts (cf. Figure 4.1).

This observation is not specific to Brazil. Figure 4.5 shows the trend growth path for Argentina. However, by simply looking at Figure 4.4 we could have already guessed that 1969, 1980, 1997 and 2007 were trend growth down-shifts, whereas 1990 and 2002 were up-shifts.

Argentina's history provides an interesting concrete example which may help us think about how this predictive model could be useful in practice. As shown in Figure 4.4, Argentina's up-shift hazard was rising and the down-shift hazard falling between 2000 and 2003. In 2001, when rating agencies slashed the country's credit rating, the rolling estimate of trend growth was 1.49% p.a. since 1996. The probability of Argentina experiencing a further one percentage point or more down-shift from this trend rate was only 2%, while the probability of the country experiencing an at least three percentage

[14]Remember that 3 percentage points is the threshold imposed for a down-shift after an up-shift when extracting trend growth. Figure 4.1 shows that 1992 was an up-shift for Brazil.

Figure 4.5 Trend growth in Argentina (1951-2015)



Notes: Trend growth (red) extracted from annual real GDP p.c. growth data (blue) using iFF.

points up-shift for at least the next 5 years was already 8%. In 2002, when Argentina declared default, the trend growth rate estimate (based on data up to and including 2001) slipped to -0.45% p.a. since 1997, while the conditional probability of an up-shift in trend growth rose to 26.2% and that of a down-shift fell to only 0.8%. In 2003, as food prices recovered (annual growth rate of 12.7% in 2002), the up-shift hazard jumped even further to 38%. Hence, as Tenreyro [40] argues: "the 2001-2002 Argentine crisis could and should have been averted [...] had international creditors (and rating agencies) waited for a couple more years", since even a simple model as the one considered here would have pointed to a higher trend growth scenario over the next few years as being much more likely that a further down-shift. And this, even before the food prices started recovering: the 2002 hazards only use 2001 data when food prices actually fell by 3.63%.

As a final example we consider China. Currently, we estimate that China has been growing at 6.81% p.a. since 2008 (last trend down-shift in 2007, cf. Table 7). The conditional probability of a further, at least 1% point, down-shift this year that would make China grow, on average, at 5.8% p.a. or less over at least the next five years is 17.3%. On the other hand, a 3 percentage points trend up-shift is a 1% probability event.

Note that the still very high trend rate at which China is currently growing is certainly contributing to the relatively large down-shift hazard.[15] However, several other factors

[15]According to our estimates in Table 7, China is currently ranked fifth in terms of highest trend growth rate, just below Ethiopia (8.02% p.a. since 2004) and slightly overtaking Myanmar (6.80% p.a. since 2011).

taken into account in our model are also hampering China's growth prospects. To see this, we can compare China with other countries that are also growing at high trend growth rates currently but have relatively low down-shift hazards. For instance, India has been growing at 5.32% p.a. since 1994 but has a conditional probability of experiencing a trend growth down-shift of only 5.2%. The difference between hazard estimates arises because India has a much higher Polity 2 score than China (9 versus -7). Moreover, in 2015, China experienced a much larger build up of domestic credit to the private sector than India: 13.41% pts. rise in China vs. 0.85% pts. increase in India. Finally, India's growth is also much less volatile China's: standard deviation of 3.24 against 6.15 in China.

In 2016, the average estimated down-shift hazard was still above its up-shift counterpart: 0.07 versus 0.043. However, Figure 4.2 suggests that the down-shift hazard has been on average falling and the up-shift hazard rising since 2013. A relatively mild external environment in 2015 with, for instance, a US 3-month T-bill average rate of only 0.05% that actually fell by 0.03 percentage points throughout the year, has certainly aided this trend. However, future rises in US rates will negatively affect growth prospects, while rising commodity prices may negatively impact non-commodity exporters. Moreover, gold prices are still at historically high levels, indicating a high level of risk aversion, which may also be detrimental to trend growth.

5. Conclusion & Future Research

Assessing a country's growth prospects is challenging because trend growth is inherently unobserved, and a large number of different domestic and external factors come into interplay at the very same time and could either improve the country's trend growth rate, or worsen it, or counterbalance each other and make the country vibrate around the current trend rate for another several years. Disagreement about a country's growth outlook often arises because different people weight these factors differently and/or use different techniques to extract the trend component from growth time series data.

This paper embraces the basic definition of trend growth as a medium/long term average growth rate and develops a comprehensive empirical methodology which allows us to address the following two questions: *What is the trend growth rate at which a country is currently growing? How likely is it to shift and in what direction?*

The methodology proposed has two components: a trend extraction method that builds on the "Fit and Filter" (FF) approach developed in Kar, Pritchett, Raihan, and Sen (2013) to identify the dates at which trend growth changes significantly, then extract the trend from growth time series as a sequence of medium/long term averages, and an econometric framework, which employs an extended version of discrete-time duration analysis to model and estimate the up and down-shift hazards - the conditional probabilities of up and down-shifts in trend growth next year, conditional on the country having already grown at the current trend growth estimate since the last trend shift.

We employ this methodology on most recent data (up to and including 2015) to give trend growth estimates for 153 countries and up and down-shift hazard estimates for 120 of them. The predictive model developed so far relates the up and down-shift hazards to 20 different variables capturing the current growth environment, the level of development, demographics, institutions, political stability, economic management, and external shocks, and explains almost 20% of trend growth dynamics.

Future research could certainly extend the set of variables considered and build more interesting and comprehensive models.

6. Appendix

6.1. **Estimation.** To construct the likelihood function in our case, let's start by considering one specific trend growth episode.

Remember that a trend growth episode starts in the year following the last trend shift $T_{j-1}+1$ or the beginning of the sample if $T_{j-1}=T_0$ - the year in which we have GDP p.c. data for the first time. It ends in the year of the new trend shift T_j or with the end of the sample if $T_j = T$. The likelihood contribution of a trend growth episode depends on how it ends.

Consider, an episode that ends at T_j with a trend up-shift. For this to happen, the country must have survived at a constant trend growth rate from $T_{j-1}+1$ to T_j-1, and conditional on this, experienced a trend up-shift at T_j. Since $\Pr(T_j - T_{j-1} \geq \delta) = 1$, the probability of this scenario reduces to:

$$
\begin{aligned}
\mathcal{L}_j^U &= \alpha^U(T_j) \times \prod_{k=T_{j-1}+1+\delta}^{T_j-1} (1-\alpha(k)) \\
&= \frac{\alpha^U(T_j)}{(1-\alpha(T_j))} \times \prod_{k=T_{j-1}+1+\delta}^{T_j} (1-\alpha(k))
\end{aligned}
$$

Similarly for the likelihood contribution of a trend growth episode ending with a trend down-shift. In the last case of a trend growth episode ending with the end of the sample, the only thing that we really know is that the trend growth duration of the censored episode is at least $T_j - T_{j-1}$ years with $T_j = T$ this time. Hence its likelihood contribution is simply:

$$
\mathcal{L}_j^C = \prod_{k=T_{j-1}+1+\delta}^{T_j} (1-\alpha(k))
$$

Putting together $\mathcal{L}^U$, $\mathcal{L}^D$ and $\mathcal{L}^C$, we can write the likelihood contribution of any trend growth episode as:

$$(6.1)\quad \mathcal{L}_j = \left[\frac{\alpha^U(T_j)}{(1-\alpha(T_j))}\right]^{\mathrm{I}[\Delta\tau(T_j)>0]} \times \left[\frac{\alpha^D(T_j)}{(1-\alpha(T_j))}\right]^{\mathrm{I}[\Delta\tau(T_j)<0]} \times \prod_{k=T_{j-1}+1+\delta}^{T_j} (1-\alpha(k))$$

where I[.] is the indicator function.

Now, let's consider country i with trend shifts $\mathscr{T}_i = \{T_{i1}, ..., T_{im}\}$. The likelihood contribution of its trend growth path is:

$$(6.2)\qquad \mathcal{L}_i = \prod_{T_j \in \mathscr{T}_i} \mathcal{L}_j$$

Finally, the likelihood function that we need to maximize is:

$$(6.3)\qquad \mathcal{L} = \prod_{i=1}^{n} \mathcal{L}_i$$

where n is the number of countries in our sample.

Taking logarithms and re-arranging:

(6.4)

$$\log \mathcal{L} = \sum_{i=1}^{n} \sum_{T_j \in \mathscr{T}_i} \sum_{k=T_{j-1}+1+\delta}^{T_j} \{\mathrm{I^U} \log \alpha^U(k) + \mathrm{I^D} \log \alpha^D(k) + (1-\mathrm{I^U}-\mathrm{I^D}) \log(1-\alpha^U(k)-\alpha^D(k))\}$$

where $\mathrm{I^U} = \mathrm{I}[\Delta\tau(k) > 0]$ and $\mathrm{I^D} = \mathrm{I}[\Delta\tau(k) < 0]$.

The vectors of parameters β^U and β^D can be estimated by substituting the hazard functions 4.5 into eq.6.4 and maximizing it with respect to them.

Several sources in the survival literature, including Allison [6], Jenkins [27], and Allignol et al.[5] explain how such discrete-time competing risk models can be estimated in practice by using standard statistical software for multinomial logits on appropriately re-organized datasets.

6.2. **Estimated trend growth rates and trend shift hazards.**

Table 7: Trend growth & conditional probabilities of trend shifts

	Trend	*Last Shift*		*Up-Shift Hazard*			*Down-Shift Hazard*		
Country	*Growth*	Year	Magnitude	Average	2015	2016	Average	2015	2016
Albania	3.01	2008	-4.26	0.034	0.048	0.049	0.123	0.059	0.049
Algeria	1.94	1994	4.29	0.07	0.02	0.025	0.177	0.072	0.088
Angola	0.75	2008	-7.97	0.036	0.015	0.019	0.272	0.204	0.169
Argentina	2.03	2007	-5.5	0.108	0.031	NA	0.087	0.136	NA
Armenia	0.64	2008	-11.94	0.1	0.1	0.155	0.213	0.09	0.026
Australia	1.92	1951	NA	0.006	0	0	0.012	0.013	0.011
Austria	0.08	2008	-2.06	0.017	0.015	0.017	0.047	0.041	0.034
Azerbaijan	1.05	2009	-19.1	0.161	0.107	0.162	0.332	0.121	0.069
Bahrain	-0.09	1993	-3.89	0.136	0.035	0.044	0.074	0.165	0.067
Bangladesh	4.86	2003	2.11	0.065	0.029	0.029	0.085	0.116	0.081
Belarus	2.2	2008	-8.24	0.058	0.04	0.095	0.304	0.176	0.07
Belgium	1.55	1974	-2.11	0.001	0.001	0.001	0.03	0.053	0.041
Benin	1.31	1960	NA	0.049	0.001	0.001	0.048	0.017	0.011
Bhutan	5.23	1990	-5.87	0.012	0.01	0.01	0.134	0.064	0.059
Bolivia	3.14	2003	1.67	0.1	0.015	0.016	0.065	0.088	0.053
Bosnia and Herzegovina	0.66	2008	-4.03	NA	NA	NA	NA	NA	NA
Botswana	2.83	1989	-7.6	0.019	0.006	0.006	0.063	0.036	0.028
Brazil	1.76	1992	3.62	0.079	0.032	0.028	0.113	0.077	0.016
Bulgaria	0.92	2008	-5.94	0.079	0.031	0.035	0.11	0.069	0.054
Burkina Faso	3.01	1994	1.96	0.052	0.01	0.015	0.083	0.096	0.058
Burundi	4.74	2010	-5.32	0.143	0.013	0.041	0.099	0.113	0.12
Cambodia	4.46	2007	-3.38	0.049	0.03	0.032	0.149	0.246	0.103
Cameroon	2.45	2010	1.34	0.103	0.01	0.031	0.096	0.101	0.105
Canada	1.93	1951	NA	0.009	NA	NA	0.019	NA	NA
Central African Rep.	-6.71	2010	-8.04	0.169	0.42	0.387	0.032	0.01	0.016
Chad	3.31	2010	-1.13	0.117	0.008	0.019	0.143	0.282	0.18
Chile	2.63	1997	-3.51	0.086	0.018	0.017	0.104	0.054	0.046
China	6.81	2007	-3.14	0.039	0.008	0.01	0.173	0.336	0.173
China. Hong Kong	1.96	2007	-4.5	NA	NA	NA	NA	NA	NA
Colombia	3.43	2002	4.19	0.033	0.013	0.019	0.042	0.047	0.038
Comoros	-0.57	1984	-1.55	0.075	0.019	NA	0.028	0.017	NA
Congo	2.13	1999	4.1	0.09	0.009	0.013	0.157	0.199	0.142
Costa Rica	2.63	1983	5.45	0.027	0.003	0.002	0.018	0.015	0.013
Côte d'Ivoire	3.01	2007	4.98	0.102	0.017	0.021	0.078	0.229	0.179
Croatia	-1.5	2008	-5.97	0.074	0.067	0.07	0.102	0.06	0.041
Cyprus	-3.32	2008	-5.86	0.041	0.121	0.106	0.1	0.016	0.041
Czech Republic	0.37	2007	-4.89	0.069	0.029	0.027	0.09	0.16	0.138
D.R. of the Congo	4.69	2009	2.74	0.265	0.016	0.016	0.078	0.202	0.167
Denmark	1.49	1969	-3.36	0.014	0.001	0.001	0.031	0.019	0.015
Djibouti	4.31	2005	3.04	0.106	0.027	NA	0.068	0.087	NA
Dominican Republic	4.32	2004	3.03	0.045	0.01	0.013	0.111	0.185	0.099
Ecuador	1.32	1976	-7.81	0.051	0.005	NA	0.092	0.038	NA
Egypt	0.31	2010	-2.65	0.029	0.051	0.055	0.129	0.204	0.111
El Salvador	1.76	1995	-3.11	0.091	0.015	0.014	0.035	0.034	0.024
Equatorial Guinea	-4.32	2009	-18.91	0.094	0.028	0.208	0.492	0.228	0.012
Estonia	0.56	2007	-8.28	0.057	0.029	0.032	0.19	0.131	0.103
Ethiopia	8.02	2003	8.47	0.15	NA	NA	0.081	NA	NA
Fiji	1.99	1987	3.32	0.069	0.013	0.014	0.063	0.074	0.065
Finland	-1.01	2007	-4.69	0.029	0.015	0.015	0.054	0.044	0.043

Country	*Trend* *Growth*	*Last Shift* Year	Magnitude	*Up-Shift Hazard* Average	2015	2016	*Down-Shift Hazard* Average	2015	2016
France	-0.06	2007	-1.8	0.017	0.013	0.015	0.083	0.134	0.063
Gabon	3.49	2009	6.43	0.072	0.017	0.022	0.217	0.237	0.177
Gambia	-0.02	1961	NA	0.052	0.002	NA	0.024	0.033	NA
Georgia	4.72	2007	-6.16	0.166	0.026	0.047	0.176	0.208	0.098
Germany	1.25	1991	-1.22	0.029	0.005	0.006	0.071	0.131	0.092
Ghana	4.88	2007	2.79	0.117	0.032	NA	0.068	0.101	NA
Greece	-3.17	2007	-6.67	0.053	0.042	0.037	0.095	0.051	0.06
Guatemala	1.33	1986	4.77	0.049	0.006	0.006	0.07	0.046	0.034
Guinea	-0.88	2008	-1.2	0.058	0.009	0.11	0.036	0.033	0.019
Guinea-Bissau	0.89	2003	3.45	0.13	0.065	0.066	0.051	0.04	0.042
Haiti	2.31	2010	3.67	0.193	0.046	0.096	0.042	0.066	0.079
Honduras	1.49	1986	3.11	0.04	0.011	NA	0.047	0.025	NA
Hungary	0.65	2006	-3.7	0.091	0.023	0.029	0.063	0.16	0.046
India	5.32	1993	3.27	0.038	0.004	0.004	0.033	0.071	0.052
Indonesia	4.09	2001	5.22	0.074	0.019	0.02	0.099	0.139	0.063
Iran (Islamic Rep. of)	0	2007	-5.42	0.142	0.115	NA	0.179	0.232	NA
Iraq	2.05	2008	-10.35	0.017	0.064	0.051	0.475	0.124	0.097
Ireland	-0.15	2007	-3.62	0.01	0.008	0.009	0.044	0.063	0.02
Israel	1.8	1973	-6.24	0.022	0.001	0.001	0.092	0.09	0.068
Italy	-1.29	2007	-1.84	0.026	0.016	0.018	0.06	0.085	0.034
Jamaica	-0.75	2007	-1.07	0.063	0.063	0.054	0.034	0.017	0.014
Japan	0.7	1991	-2.97	0.027	0.003	0.003	0.065	0.055	0.103
Jordan	-0.12	2008	-4.44	0.112	0.046	0.041	0.158	0.104	0.105
Kazakhstan	3.09	2007	-6.32	0.117	0.024	0.031	0.232	0.189	0.124
Kenya	2.64	2003	3.39	0.053	0.019	0.019	0.069	0.149	0.073
Kuwait	-3.43	2006	-9.25	0.15	0.253	0.143	0.244	0.027	0.18
Kyrgyzstan	3.27	1995	16.59	0.155	0.034	0.038	0.055	0.05	0.062
Lao People's DR	5.23	1993	3.37	0.03	NA	NA	0.103	NA	NA
Latvia	0.65	2007	-10.65	0.095	0.032	NA	0.213	0.108	NA
Lebanon	-3.06	2010	-8.95	0.2	0.295	0.241	0.179	0.036	0.06
Lesotho	3.73	2005	1.16	0.032	0.037	NA	0.08	0.055	NA
Liberia	4.98	2007	8.67	0.081	0.038	NA	0.166	0.124	NA
Lithuania	2.59	2007	-7.17	0.073	0.018	NA	0.189	0.151	NA
Madagascar	-1.17	2008	-4.46	0.113	0.123	0.114	0.028	0.039	0.039
Malawi	0.66	2009	-3.1	0.112	0.058	NA	0.094	0.071	NA
Malaysia	2.56	1997	-3.73	0.035	0.016	0.021	0.141	0.111	0.073
Mali	2.01	1984	3.67	0.079	0.006	0.007	0.053	0.081	0.099
Mauritania	1.53	2007	-3.89	0.086	NA	NA	0.157	NA	NA
Mauritius	3.72	1988	-3.13	0.036	0.006	0.007	0.043	0.026	0.033
Mexico	1.15	1986	3.73	0.038	0.01	0.011	0.101	0.059	0.024
Mongolia	8.82	2010	3	0.075	0.013	0.016	0.111	0.13	0.055
Montenegro	0.89	2008	-4.01	NA	NA	NA	NA	NA	NA
Morocco	3.24	1995	3.81	0.04	0.013	0.013	0.088	0.045	0.037
Mozambique	4.46	2001	-4.43	0.043	0.011	0.013	0.13	0.106	0.174
Myanmar	6.8	2010	-4.3	0.249	0.039	NA	0.253	0.417	NA
Namibia	3.34	2003	2.14	0.032	0.014	0.011	0.103	0.09	0.1
Nepal	2.86	1983	2.45	0.052	0.009	0.009	0.039	0.046	0.061
Netherlands	1.52	1973	-2.35	0.016	0.001	0.001	0.032	0.022	0.014
New Zealand	1.22	1966	-3.49	0.016	NA	NA	0.017	NA	NA
Nicaragua	2.51	1993	6.32	0.097	0.017	0.018	0.066	0.08	0.032

Country	*Trend* *Growth*	*Last Shift* Year	Magnitude	*Up-Shift Hazard* Average	2015	2016	*Down-Shift Hazard* Average	2015	2016
Niger	1.87	2004	2.09	0.16	0.023	0.031	0.055	0.087	0.052
Nigeria	3.11	2006	-5	0.134	0.01	NA	0.162	0.305	NA
Norway	-0.33	2007	-3.23	0.008	NA	NA	0.031	NA	NA
Oman	-4.38	2010	-6.84	0.037	0.228	0.151	0.2	0.014	0.049
Pakistan	2.44	1960	2.18	0.029	0.001	0.001	0.057	0.038	0.011
Panama	5.74	2003	4.2	0.043	0.006	0.007	0.139	0.233	0.125
Paraguay	4.99	2009	1.85	0.062	0.018	0.025	0.1	0.119	0.09
Peru	4.37	2002	3.8	0.098	0.018	0.018	0.087	0.142	0.135
Philippines	3.76	2002	2.7	0.068	0.015	0.013	0.06	0.075	0.102
Poland	4.18	1993	6.87	0.073	0.007	0.008	0.071	0.069	0.053
Portugal	0.01	2001	-2.23	0.041	0.014	0.016	0.093	0.039	0.032
Qatar	1.6	2001	-5.93	0.168	0.042	0.041	0.109	0.154	0.088
Republic of Korea	3.63	1996	-4.74	0.034	0.01	0.011	0.19	0.132	0.091
Republic of Moldova	2.99	2008	-3.68	0.336	0.102	0.187	0.036	0.039	0.026
Romania	1.25	2008	-6.14	0.074	0.033	0.036	0.12	0.096	0.072
Russian Federation	0.33	2008	-6.89	0.144	0.069	0.146	0.186	0.091	0.026
Rwanda	4.29	2008	-1.29	0.069	NA	NA	0.113	NA	NA
Saudi Arabia	2.22	2002	4.16	0.077	0.009	0.008	0.159	0.114	0.182
Senegal	1.32	1993	3.93	0.084	0.013	0.015	0.045	0.046	0.039
Serbia	0.17	2008	-6.03	0.052	0.088	0.091	0.128	0.053	0.084
Sierra Leone	3.41	2004	-4.8	0.188	0.014	0.113	0.074	0.145	0.003
Singapore	2.68	1997	-3.8	0.035	0.009	0.009	0.179	0.096	0.062
Slovakia	1.45	2008	-5.52	0.068	0.043	NA	0.098	0.072	NA
Slovenia	-0.91	2008	-5	0.053	0.038	0.044	0.087	0.108	0.046
South Africa	1.51	1993	3.18	0.032	0.017	0.019	0.039	0.029	0.017
Spain	-0.75	2007	-2.82	0.037	0.029	0.028	0.084	0.04	0.04
Sri Lanka	6.05	2004	2.07	0.04	0.012	0.01	0.063	0.291	0.324
Sudan (Former)	-1.22	2010	-5.02	0.094	0.073	0.082	0.123	0.105	0.066
Swaziland	1.26	1990	-4.44	0.019	0.008	0.009	0.108	0.094	0.067
Sweden	2.15	1951	NA	0.01	0	0	0.034	0.011	0.015
Switzerland	0.86	1973	-2.26	0.005	0	0	0.008	0.007	0.005
Syria	-8.36	2009	-9.98	0.086	NA	NA	0.169	NA	NA
Taiwan	3.87	1995	-3.08	NA	NA	NA	NA	NA	NA
Tajikistan	3.07	2008	-3.42	0.061	0.048	0.084	0.174	0.144	0.053
TFYR of Macedonia	1.99	2008	-3.09	0.119	0.047	0.056	0.061	0.136	0.049
Thailand	3.67	2001	4.4	0.067	0.037	0.028	0.157	0.204	0.218
Togo	2.54	2009	3.48	0.124	0.035	0.042	0.062	0.104	0.08
Trinidad and Tobago	0.57	2006	-8.91	0.065	0.028	0.028	0.073	0.038	0.026
Tunisia	0.82	2010	-1.86	0.041	0.095	0.107	0.131	0.098	0.041
Turkey	1.92	2006	-3.85	0.053	0.044	0.041	0.105	0.132	0.198
Turkmenistan	9.56	2004	4.78	NA	NA	NA	NA	NA	NA
Tanzania	3.37	1998	2.38	0.051	0.008	0.011	0.083	0.145	0.13
Uganda	1.48	2010	-3.5	0.101	0.022	0.034	0.112	0.274	0.139
Ukraine	-1.58	2007	-9.95	0.249	0.242	0.317	0.113	0.036	0.013
United Arab Emirates	2.43	2010	11.47	0.211	0.093	0.101	0.088	0.087	0.05
United Kingdom	2	1951	NA	0.005	0.004	0	0.02	0.019	0.004
United States	2.03	1951	NA	0.001	0	0	0.008	0.002	0.001
Uruguay	4.91	2003	8.04	0.09	0.008	0.009	0.092	0.141	0.108
Uzbekistan	6.57	2003	3.91	NA	NA	NA	NA	NA	NA
Venezuela	-2.1	2008	-10.77	0.08	NA	NA	0.084	NA	NA
Viet Nam	5.65	1991	2.28	0.018	0.006	0.006	0.092	0.065	0.062

Country	*Trend Growth*	*Last Shift* Year	Magnitude	*Up-Shift Hazard* Average	2015	2016	*Down-Shift Hazard* Average	2015	2016
Yemen	-4.57	2010	-6.5	0.046	NA	NA	0.138	NA	NA
Zambia	4.38	2002	3.22	0.094	0.009	0.011	0.092	0.124	0.1
Zimbabwe	12.13	2008	17.54	0.135	NA	NA	0.069	NA	NA

Notes: Trend growth estimates based on data up to and including 2015, except for Syria (growth data stops in 2014). Hazard estimates based on model in Table 5. Trend rates extracted using iFF with the following assumptions:
Minimum trend growth duration: 5 years
Trend shifts significance filter: 1% pt. change for a shift in the same direction. 3% pts. change for a shift in the opposite direction.
Example of how to read the table: China has been growing at 6.81% p.a. since 2008 (last trend shift in 2007). 2007 was a trend down-shift, hence a further down-shift would be identified as a $\leq$ 5.81% p.a. average growth rate over the next $\geq$ 5 years, whereas an up-shift would be a $\geq$ 9.81% p.a. average growth rate over the same period. In 2016, the conditional probabilities of trend down and up-shifts are 17.3% and 1% respectively.

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