Empirical Analysis of Dynamic Macroeconomic Growth and Business Cycle Processes

- Using Modern Non- and Semiparametric Approaches -

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Abstract

This thesis empirically analyzes the dynamics of macroeconomic processes using modern non- and semiparametric approaches. The main challenge for the analysis of macroeconomic variables is their trending behavior over time, which render parametric model fitting a complex task. Therefore, macroeconomic time series need to be detrended for further analysis and thus divided into different components, a deterministic and a stochastic part. The introduction of a recently developed local polynomial method for the deterministic trend estimation with an iterative plug-in (IPI) algorithm for bandwidth selection and the subsequent parametric analysis of the residual component solve this challenge. Thus, a flexible, statistically and economically based approach is used for the empirical investigation of macroeconomic dynamics concerning growth and business cycle theory. Therefore, a data-driven IPI bandwidth selection algorithm is developed in order to estimate a suitable trend function without prior model assumptions. This nonparametric estimation approach is introduced theoretically and its advantages are demonstrated in an extensive simulation study. After the trend is estimated and removed from the original data, any model can be fitted to the standardized residuals, known as the cyclical component. Using a Self-Exciting Threshold Autoregressive (SETAR) model for the subsequent parametric cycle analysis provides evidence for asymmetric business cycles. This leads to quite different policy implications than those implied by standard approaches due to the appropriate identification of the actual position on the cycle, e.g. investment decisions. Furthermore, the nonparametric analysis of the trend sheds light on long-term growth processes and provides significant evidence for the recent phenomenon of secular stagnation. The advantages of this approach combined with a newly developed linearity test determine the starting point and magnitude of secular stagnation. The stable trend estimation and the appropriate bandwidth selection demonstrate the advantages of the fully endogenous local polynomial trend estimation approach for the analysis of dynamic macroeconomic processes. Furthermore, its flexibility and direct relation to macroeconomic growth theories encourage the use of this fully data-driven method.

1 Introduction

In a 2009 New York Times Magazine article Paul Krugman stated about the financial crisis and the subsequent recession that hit the world economy in 2007/2008, “macroeconomics, which should have been providing clear guidance about how to address the slumping economy, was in its own state of disarray” (Krugman, 2009). Consequently, after the financial crisis and the Great Recession in 2008, growth dynamics and business cycle analysis regained attention. Although their investigation is a long-standing topic in macroeconomics, structural changes due to e.g. technological development and the integration of financial markets, require continuous modifications. The direct impact of growth on the standard of living, income distribution and hence inequality bases the society’s decision on the proper analysis of growth and cyclical phenomena and the identification of possible distortions (Gordon, 2015). Those distortions comprise Summers’ (2014, 2015) and Gordon’s (2012, 2015) current debate on the secular stagnation hypothesis concerning the possibility of a persistent slowdown in output and productivity growth.

In addition, the availability of data covering a long period of time and advances in statistical methods due to computational feasibility enlarge statistical inference. These statistical improvements prove and modify stylized facts and consequently macroeconomic theory, which result in revised monetary and fiscal policy implications. After the Great Recession, a consensus among economists and politicians emerged that dynamic growth and cyclical processes need to be understood in more detail. Victor Zarnowitz, from the University of Chicago and the National Bureau of Economic Research (NBER) and Ataman Ozyildirim, director of the economic and global research chair at the Conference Board, argued that

> *“One can only welcome the revival of interest in methods of filtering and detrending economic and financial indicators that is associated with recent research in business cycles. However, these methods too often abstract from the main difficulty of time series decomposition, which is that trends and cycles interact and influence each other”* (Zarnowitz and Ozyildirim, 2006, p. 1719).

Nevertheless, the new opportunities for macroeconomic analysis also pose several challenges. Particularly, the data covering a time span of over 200 years may exhibit special characteristics, which need to be taken into account. These economic time series follow a specific trend that is characterized by the underlying growth dynamics, but also influenced by innovations, policy changes, economic and historical events (Gallegati et al., 2017). By not considering this trend, the quality of the fitted model is impaired due to biased estimators. Therefore, a component model is a possible solution. Following Morley and Piger (2012), economic activity is separated into a growth component, measuring long-term trend dynamics, and a business cycle component for depicting short-term fluctuations. Depending on the data, seasonal patterns might need to be considered, as well. As mentioned by Zarnowitz and Ozyildirim (2006), the transitory business cycle fluctuations away from a long-run trend are not independent of long-run growth. These special features rule out the use of most already established econometric models, e.g. time series models that assume stationary data, and require new methods which are able to deliver useful information about the underlying long-term growth pattern and short-term cyclical movements. In order to analyze both components, the crucial point is to decompose the underlying time series into long-term dynamics and short-term (stationary) fluctuations. Zarnowitz and Ozyildirim (2006) postulate that a good trend "should be influenced by the cyclical movements in the data but it should also be smooth" (Zarnowitz and Ozyildirim, 2006, p. 1732). Moreover, an appropriate trend should be piecewise linear and does not need to be stochastic.

In accordance with Canova (1998a) and Morley and Piger (2012) the decomposition is an old topic, where the estimated trend and business cycle severely depend on the model specification. Different filters yield varying solutions and the selection of the detrending method is not independent of the further analysis. As Mills (2009) states, instable and incorrect detrending approaches impede the decomposition. Consequently, Kaiser and Maravall (2001) and Metz (2011) argue that subsequent formal analysis of economic cycles is a frustrating issue due to different results for different detrending methods. Although this is a long-standing discussion, Canova (1998a, b), Burnside (1998) and Álvarez and Gómez-Loscos (2018) show the existence of many problems with commonly used detrending methods. Further, Phillips (2003) claims that although trends need to be usually considered in empirical analysis, they are not really understood and Phillips (2001) postulates that "the real trend in the data is far more complex than" detrending methods usually suggests (Phillips, 2001, p. 24).

However, recently developed nonparametric methods are able to improve the identification and estimation quality of both components substantially. In accordance with Calonico et al. (2018), these methods are more robust than their parametric counterparts since parametric methods suffer from misspecification bias. In contrast to usually used filtering methods, such as linear detrending or the Hodrick-Prescott (HP) filter (Hodrick and Prescott, 1997), the recently developed nonparametric approach allows for a correlation between permanent and transitory movements and is processed fully data-driven. Consequently, this thesis presents a statistically based approach to model economic growth and business cycles, which is statistically improved and economically justified. In contrast to the widely used assumption on the independency of both components, this doctoral thesis introduces a newly developed data-driven local polynomial method that allows for short-range dependence, deals with low-frequency challenges, enhances the estimation quality at boundary points and addresses the problem of nonstationarity. Moreover, the method is directly linked to log-linear macroeconomic growth theories.

The differences between the usually applied HP filter and the proposed local polynomial regression, which is a local linear regression (LLR) in this specific case, are displayed for the natural logarithm (LN) of the United States (US) gross domestic product (GDP) in Figure 1.1. The real GDP per capita (p.c.) data for the period from 1790 to 2017 (red dotted) are extracted from Johnston and Williamson (2019).

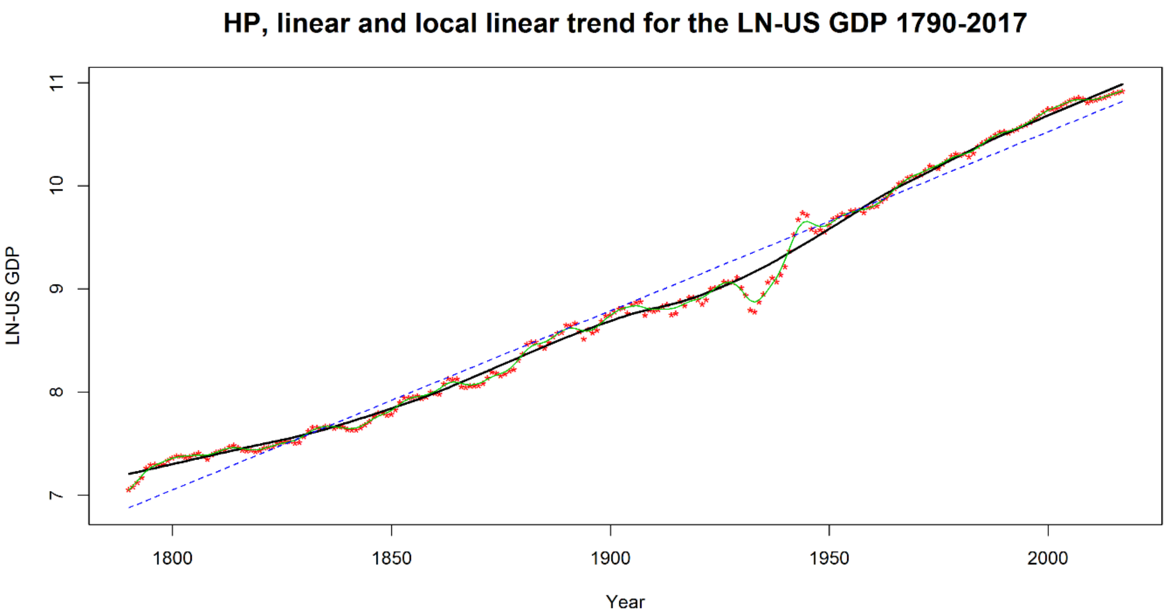

Figure 1.1: Estimated HP trend, linear trend and data-driven local linear trend for the LN-US GDP data from 1790 to 2017

Notes: Estimated HP trend $\lambda = 6.25$ (green solid), linear trend (blue dashed) and data-driven local linear trend (black solid) for the LN-US GDP data from 1790 to 2017 (red dotted).

At a first glance, all methods show an upward sloping trend function pointing towards the results of Beaudry and Koop (1993) that the impacts of negative shocks are temporary, whereas positive shocks are more persistent. Moreover, different growth periods exist, which could be exemplarily detected after the end of World War II (WWII), where an increase in output is observable. Obviously, the three diverse approaches yield quite different trend (and correspondingly cycle) estimates and the differences change over time. Hence, the policy implications depend heavily on the method under consideration. Whereas the simple linear trend (blue dashed) seems to be, in line with Jones (2002), a reasonable first approximation, it is not able to reflect the trend of US GDP data appropriately. In contrast, the HP filter (green solid) with a smoothing parameter of $\lambda = 6.25$ proposed by Ravn and Uhlig (2002), takes changes in the data into account and is close to the original observations. The data-driven local linear trend (black solid) is smoother, more robust against outliers and only influenced by the major changes in economic conditions. In accordance with the requirements of Zarnowitz and Ozyildirim (2006), it is deterministic, affected by cyclical dynamics and fits to the long-term growth movements, resulting in a stable trend.

Figure 1.2 displays the corresponding business cycles using the HP filter (green solid), the linear regression (LR, blue dashed) and the LLR (black solid). Similar to Figure 1.1, the three different trends, which are removed from the original observations in Figure 1.2, yield three different cyclical (residual) patterns.

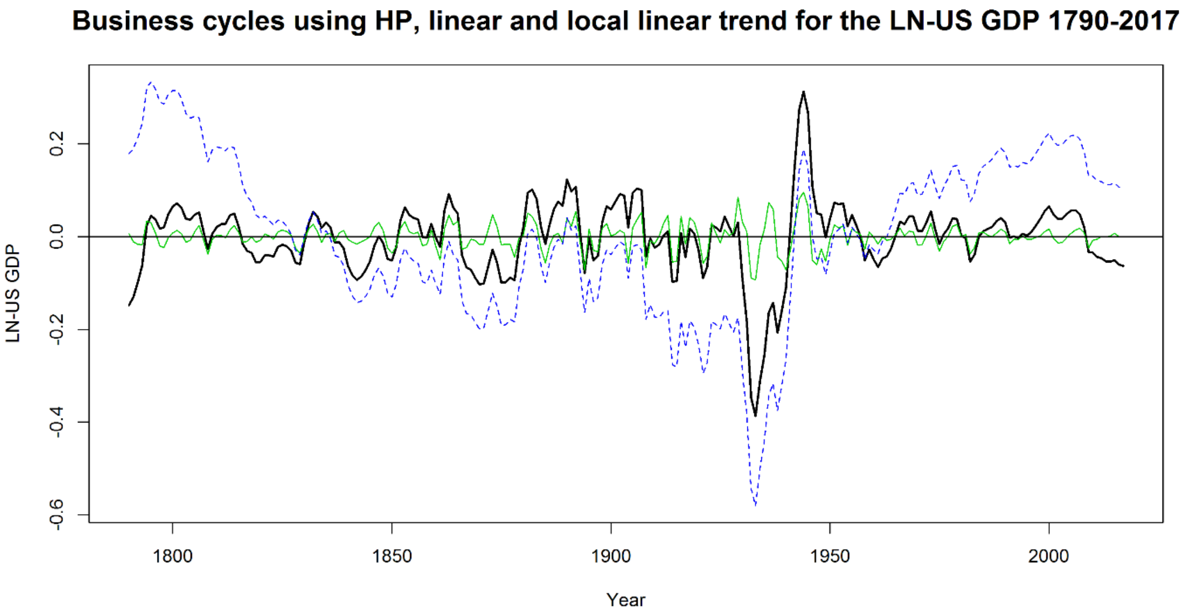

Figure 1.2: Estimated cycles using the HP trend, the linear trend and the data-driven local linear trend for the LN-US GDP data from 1790 to 2017

Notes: Estimated business cycles using the HP trend $\lambda = 6.25$ (green solid), the linear trend (blue dashed) and the data-driven local linear trend (black solid) for the LN-US GDP data from 1790 to 2017.

Whereas the linear trend does not render the cycle stationary, the HP filter and the LLR seem to be appropriate for this purpose. The cycles show the most deviations from the corresponding trend function within the period from 1930 to 1950. As explained in Pollock (2000) and shown in Figure 1.2, the HP trend attributes more dynamics to the trend, whereas less movements are ascribed to cyclical fluctuations. McCallum (2000) argues for the Great Depression in the 1930s that the HP filter excludes such extreme observations from the cycle and attributes them to the trend. Consequently, the Great Depression is described less severely than it was and macroeconomic policy decisions based on commonly used detrending methods like the HP filter, as well as the analysis of business cycle dates, may be misleading in the sense of spurious cycles. The cyclical movements delivered by the local linear trend obviously increase during this period, although the trend is affected by those market distortions. Besides these differences, it is interesting to note that for the golden episode of growth lasting from 1960 to 1980, both approaches yield quite similar results. Moreover, the increases seem to be more gradual than the subsequent downturns, indicating asymmetric business cycles. However, at the right boundary, the cycle of the LLR is very different to the cycle of the HP filter and below zero since 2008.

Figures 1.1 and 1.2 serve as a starting point for this thesis in order to introduce a modern, data-driven local polynomial regression approach and to discuss economic consequences of this more sophisticated method for the analysis of dynamic growth processes and business cycles. In other words, an ambiguous trend and cycle estimation may be followed by misleading economic policy, e.g. economic stabilization policies, which matter to society; hence their causes, consequences and the refinements of new methods are of public interest.

Therefore, this doctoral thesis focuses on the introduction of a modern semiparametric approach, its application to macroeconomic time series, the further analysis of the dynamic components and the new implications for economic policies. Throughout the thesis, the trend is estimated nonparametrically using an extended iterative plug-in (IPI) algorithm for determining the optimal bandwidth for the scale function endogenously. The bandwidth represents the smoothing parameter in this nonparametric regression and is economically linked to the optimal time length of the underlying growth process. Those data-driven estimated segments will be called continuously Moving Trends (MT) for the level data and reflect different steady state growth paths. Furthermore, statistical features, e.g. the dependence structure, are fully captured by this bandwidth. In addition, the IPI algorithm can also be applied in order to determine the bandwidth of the derivatives. These first derivatives reflect the growth rates of the underlying process and the trend of such rates is called continuously Moving Growth Rate Trend (MGT). Fitting any semiparametric model to the underlying observations is a two-step procedure. After the trend is estimated nonparametrically using the above described approach, the residuals are calculated by subtracting the trend estimates from the original observations. In a last step, the trend and the residuals could be analyzed by any suitable test method or various parametric models can be fitted to further analyze the cyclical movements in the data. As a nonparametric and a parametric estimation part exist, the notation “semiparametric” time series model is an obvious choice.

1.1 State of research

This section provides a brief overview of the literature on trend and cycle estimation methods and the macroeconomic implications of growth trends and business cycles. Note that this is a broad overview of the existing literature, while the more comprehensive summaries of the particularly relevant literature are discussed within the four studies.

1.1.1 Economic trend estimation methods

As indicated above, the estimation of trends is crucial for the analysis of macroeconomic growth processes and the subsequent business cycle analysis. Theoretically, the precise identification of a trend function is quite difficult depending on the definition of the trend. Kendall et al. (1983) define a trend as a smooth function over numerous years. Hodrick and Prescott (1997) start the development of a new filtering approach from the definition that a quarterly mean growth rate change of 0.125% is attributed to the trend component. In the frequency dimension, Pollock (2000) attributes non- and lowest frequencies to the trend function, without defining the precise interval of these lowest frequencies. The Business Dictionary (2017) announces a broad definition, where a trend is “a general direction in which a process, an average, general tendency or nation’s economy develops/moves over time”. However, Álvarez and Gómez-Loscos (2018) summarize that no general explicit definition of a trend, neither in econometric nor in economic theory, exists.

Empirically, the exact identification of a trend depends on its characteristics, its underlying definition and the sample size. In accordance with Metz (2011), especially the distinction between deterministic and stochastic processes is crucial for the trend estimation and depends on the underlying data. Amongst others, Nelson and Plosser (1982) start the discussion on whether the underlying trend function is deterministic with stationary fluctuations or stochastic with nonstationary fluctuations. Nevertheless, the exact determination remains difficult due to a lack of unit root tests under well-specified alternative hypotheses. These identification problems of the characteristics of the true data generating process (DGP) also lead to methodological problems as most methods are either specified for deterministic or stochastic processes. In accordance with Cogley and Nason (1995), Harvey and Trimbur (2003) as well as Maravall and del Río (2007), a misspecification yields spurious results and incorrect implications. Recently, Luo and Startz (2014) and Zarnowitz and Ozyildirim (2006) argue for a leastways local linear trend in US GDP data, which needs not to be inevitably stochastic.

Besides this fundamental question, since the availability of computer intensive programs various detrending procedures evolve. A point of departure is, in accordance with Jones (2002) and Fernald and Jones (2014), the linear trend. Starting in the 1980s, Beveridge and Nelson (1981) define a decomposition method based on long-horizon forecasts. In addition, low frequency as well as high frequency filtering become increasingly important depending on the research question of trend or cyclical analysis. Baxter and King (1999) summarize those frequency filters and introduce a band-pass filter, the Baxter-King (BK) filter that allows a certain range of frequencies to pass the filter. Therefore, they assume the DGP to be independent identically distributed (i.i.d.) and adopt the definition of Burns and Mitchell (1946) where US business cycles last between six and 32 quarters. Another approximation to an ideal band-pass filter is proposed by Christiano and Fitzgerald (2003) (Christiano-Fitzgerald filter, CFF), where, as in Baxter and King (1999), different frequency components sum up to the underlying time series. Separating a fixed frequency band isolates a pre-specified trend component, assuming a random walk for the true DGP. A more general type of signal processing filter is the Butterworth (BW) filter, which is defined for economic applications in Harvey and Trimbur (2003). There, several low- and band-pass filters are summarized in the class of BW filters. By contrast to those spectral analyses, Gallegati et al. (2017) propose the use of wavelet analysis for long-term economic time series. Although wavelet analysis is similar to spectral analysis, wavelets are more flexible and in accordance with Gallegati et al. (2017) able to process more complex and nonstationary signals.[1] Morley et al. (2003) and Morley (2011) stress the importance of the unobserved components (UC) model in the trend and cycle decomposition. This UC model assumes that the trend can be described by a random walk, with the possibility of a drift, and the cycle is an Autoregressive (AR) process of finite order.

In accordance with Giorno et al. (1995) and Cogley (2008) the most popular method in economics is the Hodrick and Prescott (1997) filter which was originally introduced by Hodrick and Prescott in 1981. The HP filter is widely used for economic applications by various institutions like the International Monetary Fund (IMF), the Organisation for Economic Co-operation and Development (OECD) and the European Central Bank (ECB). More recently, spline smoothing becomes increasingly important for trend estimation. In this context, Paige and Trindade (2010) claim that the HP filter is a special type of penalized

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[1] More details on commonly used detrending methods are presented in Table 1.1 in Section 1.2.1.

spline smoothing. Canova (1998a) gives a detailed description of various detrending procedures arguing in Canova (1998b) that one must be aware of the differences they generate and the assumptions they rely on. In this vein, Álvarez and Gómez-Loscos (2018) provide a recent overview of advantages and disadvantages of filtering methods. In accordance with Burnside (1998), these filters can be interpreted as numerous windows through which to look at different characteristics of the data.

1.1.2 Analysis of the cyclical component

As already noted, long-term trends and short-term business cycles influence each other, hence the trend estimation is closely related to the further analysis of the cyclical (residual) component. This analysis, reviewed in Milas et al. (2007), includes the identification of turning points, which is an important issue in timing, forecasting and interaction of macroeconomic variables. Especially, the identification and forecasting of booms and busts gives unprecedented opportunities for economists, politicians, investors and the society. While technological innovations speed up growth temporarily, distortions of supply and demand in times of conflicts or industrial dispute may temporarily impede growth. Furthermore, monetary and fiscal policy could lead to shocks to aggregate demand that become the driving forces of fluctuations in output. In addition, alternating periods of inflation and deflation influence investors and hence growth, leading to cyclical behavior. In other words, the influence of financial markets on business cycle fluctuations becomes increasingly important and may affect cyclical structures. Referring to Canova (1998a) the investigation of cycles is essential for the understanding of co-movements of macroeconomic variables, for the calculation of the degree of fluctuations and the identification of indicators that determine economic activity. Furthermore, Mills (2009) reviews the importance of cyclical analysis, since the empirical investigations of Tinbergen in the 1930s lead to “the first macrodynamic models of the business cycle” (Mills, 2009, p. 223). In other words, empirical analysis provides the groundwork of theoretical models and proves their validity.[2] In summary, business cycle identification and estimation are essential for the behavior of macroeconomic policy, financial markets and for monitoring the economy.

Economically, the form of the cycle exhibits important information on the actual state of the economy concerning for example investment and production. However, due to the lack of a general method for the trend estimation and the cyclical analysis, the results for the

[2] A detailed review on different theories for economic cycles is provided by Bernard et al. (2014). The authors distinguish between numerous cycle theories that more precisely separate between long-, medium- and more short-term (business) cycles.

subsequent business cycle are ambiguous. In this sense, the definition of the trend yields the definition of the cycle. Empirically, various models for business cycle analysis are fitted parametrically to the residuals or their growth rates after the trend function, using various detrending methods, is removed from the original observations. In accordance with Morley and Piger (2012), linear, symmetric time series models like the AR model are a point of departure. Perron and Wada (2009) argue that AR models of different lag orders p are able to capture various features of business cycles. In addition, Autoregressive Moving Average (ARMA) models are a consistent extension, frequently applied to the cyclical component by Morley et al. (2003) and Morley and Piger (2006). Under the assumption of a unit root nonstationary series, the ARMA model is generalized to the Fractional Autoregressive Integrated Moving Average (FARIMA) model. This model induces that past shocks have a permanent effect on output and are used in a study of Candelon and Gil-Alana (2004) with ambiguous results. Tsay (2005) focuses on multivariate, generalized extensions of the AR model by applying the Vector Autoregressive (VAR) model to real data. The VAR model captures multivariate relations and cross-correlations between different time series allowing for lead-lag relationships. Nevertheless, Box et al. (2008) argue that VAR models become complex systems of feedback relations, suffering from overparametrization and are only interpretable when using auxiliary concepts like structural analysis as Granger causality, impulse response functions and forecast error variance decompositions.

Mitchell (1927) initiated the discussion on the possible asymmetry of business cycles which remains a highly debated topic since almost 100 years. Keynes (1936) suggests asymmetric cycles, arguing in favor of short and volatile recessions with a high amplitude compared to slow and gradual expansions. In the 1980s this discussion was further developed by Neftçi (1984) and extended by Sichel (1993) and Jovanovic (2006), who propose additional definitions, like “deepness” and “steepness”, and tests for asymmetric business cycles. Today, as Milas et al. (2007) emphasize, the development of nonlinear, piecewise and local linear models reveals new opportunities for the analysis of the cyclical component. Hamilton (1989) introduces such a model called the Markov switching model, which switches between two regimes, contractions and expansions, in the mean with transition probability following a Markov chain. In a seminal work, Morley and Piger (2006) focus on the Threshold Autoregressive (TAR) model developed by Tong (1978). This TAR model is able to distinguish different regimes and their respective dependence structure. Using own lagged values as the threshold parameter, the parameter that separates different regimes, the TAR model is defined as a Self-Exciting Threshold Autoregressive (SETAR) model. Among

others, Potter (1995) argues that SETAR models outperform standard linear models in an application to US gross national product (GNP) data using zero as the threshold variable. In accordance with Morley and Piger (2012), nonlinear regime switching models are slightly preferred over linear AR models because any information criteria, like the Akaike Information Criterion (AIC) or the Bayesian Information Criterion (BIC), select a nonlinear model. This model preference and the optimal number of regimes, which varies in accordance with Koop and Potter (2006), could be tested using Hansen's (1997) procedure. Therefore, Hansen's (1997) test is able to distinguish between linear and nonlinear models. Although arguments in favor of asymmetric behavior exist, the evidence is far from being conclusive as related methods yield various different coefficients. It is important to note the existence of numerous other cyclical phenomena. However, as mentioned in Gallegati et al. (2017) and Metz (2011), these analyses obey the same methodological detrending and cyclical identification requirements, but have different theoretical foundations. For more details and an example of financial cycles, the interested reader is referred to Schularick and Taylor (2012).
The investigation of business cycles is also closely related to the output gap analysis. Thereby, the output gap is defined as the gap between potential output and actual output. In economic theory, the concept of potential output reflects the aggregate supply ability under stable inflation and flexible prices (Álvarez and Gómez-Loscos, 2018). In accordance with Orphanides and van Norden (2002), reliable real-time estimates of the trend and the cycle are required in order to implement efficient stabilization policies. Recently, Alichi (2015) and especially Álvarez and Gómez-Loscos (2018) summarize different univariate and multivariate methods as well as latest findings concerning the output gap, and hence the cycle estimation. Summing up numerous requirements, advantages and drawbacks, they conclude that univariate methods are useful due to the heterogeneity of countries. However, such methods need to be more tightly linked to economic theory. In this vein, the short-term component delivers information on the speed of development or possible recoveries and is a major pillar of monetary policy.

1.2 Relevant gaps in the literature

The current state of research demonstrates various approaches by clarifying that no satisfactory trend and cycle definition exist. Consequently, there is no appealing general detrending method for the analysis of long-term growth trend and short-term business cycle components. This results in numerous, sometimes spurious, stylized facts concerning economic growth and business cycles. Hauk and Wacziarg (2009) summarize the numerous drawbacks of growth analysis, which include "the excessive distance between measured variables and the theoretical concepts they are meant to capture; poor grounding of estimated functional forms in economic theory […]; unjustified claims of causality in explanations of growth; a small number of available observations […]" (Hauk and Wacziarg, 2009, p. 104). Among other challenges, these drawbacks result in an increasing number of methodological discussions on the appropriate analysis of growth phenomena. Hence, the stylized facts of trend and growth processes are inconclusive along the profession depending on the underlying method. To sum up in line with Metz (2011), various detrending and filtering methods exist, whereas their underlying assumptions result in different trend estimators. They also lead to different conclusions about the actual state of the economy, e.g. the topic of secular stagnation, and suitable policy responses. Consequently, ambiguous results require more research on economically based and statistically reasoned detrending procedures. This section identifies the gaps in the academic literature and hence motivates this thesis. Bridging these gaps improves policy decisions by enhancing the understanding of growth and cyclical phenomena and provides the base for a revision of growth theories. The following two subsections deliver an overview, while the specific literature and its shortcomings are presented in more detail within each chapter of this thesis.

1.2.1 Methodological shortcomings

Among others, Canova (1998a), Harvey and Trimbur (2003), Alexandrov et al. (2012) and Álvarez and Gómez-Loscos (2018) demonstrate various different methods for trend estimation while their results depend on the assumptions the models impose. These assumptions usually restrict the functional form w.r.t (with respect to) the expectations derived from theoretical considerations. This is especially the case for parametric methods but also for nonparametric methods, where the choice of a smoothing parameter or bandwidth determines the shape of the resulting estimates and is usually selected arbitrarily (Flaig, 2015). For example, Cogley (2008) shows the critical dependence of the BK filter and the CFF on the pre-specified frequency band and hence on the definition of the functional form of trend and cycle. In accordance with Gallegati et al. (2017) even for wavelet filters the frequencies that identify cyclical periodicities need to be pre-specified. Therefore, wavelets depend on the component of interest for the underlying research question. A summary of well-known and frequently applied macroeconomic detrending methods, comprising their assumptions, advantages and disadvantages is provided in Table 1.1.

Table 1.1: Overview of well-known detrending methods

Method	Class	Assumption	Advantages	Shortcomings
LR (Álvarez and Gómez-Loscos, 2018)	Model-based approach	Linear trend is independent from the cycle (residual)	Simple, good first approximation	Long-run evolution is a function of time, shocks are neutral
BN Decomposition (Beveridge and Nelson, 1981; see also Álvarez and Gómez-Loscos, 2018)	Model-based approach	Trend is long-run forecast, ARIMA representation, DGP is RW, perfectly correlated innovations of trend and cycle	Trend and cycle are not independent	Pre-specification, too much variation is attributed to the trend, different results based on different ARIMA specifications
HP filter (Hodrick and Prescott, 1997; see also Guay and St.-Amant, 2005; Álvarez and Gómez-Loscos, 2018)	Spline smoothing	Series is an I(2) process, trend is stochastic, trend and cycle are independent	Simple, uniform framework	Arbitrary selection of smoothing parameter, boundary problems, induces spurious cycles, problems if the spectrum is dominated by low-frequencies
BK filter (Baxter and King, 1999; see also Guay and St.-Amant, 2005; Álvarez and Gómez-Loscos, 2018)	Band-pass filter	Approximation to an ideal band-pass filter, DGP is i.i.d., business cycles between 6-32 quarters	Transparent over the range of frequencies, application to different frequencies	Pre-specification of pass-band, boundary problems, do not isolate the cycle for stochastic processes, problems if the spectrum is dominated by low-frequencies
CFF (Christiano and Fitzgerald, 2003)	Band-pass filter	Approximation to an ideal band-pass filter, DGP is a RW, long cycles	Transparent over the range of frequencies, application to different frequencies, converges in the long run to the optimal filter, applicable to a broader class of time series than the BK filter	Pre-specification of pass-band, boundary problems
BW filter (Harvey and Trimbur, 2003; Álvarez and Gómez-Loscos, 2018)	Low-, and band-pass filter	DGP is a RW	Better approximation to an ideal gain function, less backcasts and forecasts than in BK filter, flexible	Pre-specification of pass-band
Wavelet analysis (Gallegati et al., 2017; Crowley, 2007; Cogley, 2008; Álvarez and Gómez-Loscos, 2018)	Wavelet-based method	Local projections, basis functions are orthogonal	Accounts for variation of the frequency (robust), not restricted to sines and cosines (model-free), generalization of Fourier analysis, no assumptions on the type of the signal	Pre-specification of cyclical-periodicities, all fluctuations are cyclical, choice of wavelets (symmetric, asymmetric), complex functional form of wavelets, length of wavelet

Notes: Overview of detrending and filtering methods frequently applied in macroeconomics based on the summary given by Álvarez and Gómez-Loscos, 2018.

Durlauf et al. (2005) provide a comprehensive overview of modern growth econometrics. They state the importance of the functional form for economic theories and argue that researchers do not agree on the empirical specification. In the sense of Metz (2011), this specification concerning form and correlation determines the level of persistence and consequently the effects of shocks. Whereas neoclassical growth theories (Solow, 1956) rely on a linear DGP, endogenous growth models (Romer, 1986) induce nonlinearities. A broader approach should be fully data-driven, more flexible and should not restrict the shape, the range or the functional form of the trend or the cyclical component. In other words, a nonparametric approach, able to depict both theories, is preferred for the trend estimation, where the remaining choices of key constants, e.g. the bandwidth or smoothing parameter, need to be optimal in a data-driven-sense. The more flexible and general approach presented throughout this thesis is adopted from the analysis of financial markets (Feng, 2014) and consists of a nonparametric and a parametric part. This semiparametric estimation approach is a two-step procedure that estimates a deterministic long-term trend and a stochastic short-term cyclical component. Since it is a two-step procedure, the estimation averts numerical problems that might in accordance with Hautsch and Pohlmeier (2001), become apparent in the joint estimation of both components. Moreover, the fully data-driven method is able to take the special characteristics of the underlying data into account by relaxing prior assumptions. Hence, the selection of the smoothing parameter or bandwidth, based on Gasser et al. (1991), is in line with the underlying properties and processed endogenously by minimizing the asymptotic mean integrated squared error (AMISE).

Within this bandwidth selection formula two unknown quantities, the variance factor, displaying the value of the spectral density (Bühlmann, 1996), and a derivative of the trend function are present. Obviously, the variance factor, which is the sum of the autocovariances, is difficult to estimate because it depends on the correlation of the errors. In order to calculate this sum, the maximal lag length needs to be determined in advance. In accordance with Feng (2014), the maximal lag of the lag-window estimator is set to a fixed value by the researcher and normally verified using a simulation study. Throughout this thesis, in order to further automatize the estimation procedure, the variance factor is estimated nonparametrically by removing the parametric restriction at this stage. Hence, the trend estimation is further automatized by introducing another IPI algorithm, based on Bühlmann (1996). This modified IPI algorithm allows a data-driven selection of the optimal window-width in order to improve the calculation of the variance factor.

Another gap in the literature on detrending approaches is that a variety of methods is theoretically designed for an infinitely long time series. In accordance with Mise et al. (2005), the HP filter requires an infinite number of observations of the analyzed series. Furthermore, Christiano and Fitzgerald (2003) present the practical limitation of ideal band-pass filters, since ideal is associated with an infinite sample size and argue in favor of an approximation. Although the assumption of an infinitely long series is crucial for theoretical considerations, adjustments can improve the application to data series with a relatively small number of observations. These approximations are especially important for macroeconomic data, where the observations are typically recorded at low frequencies and the resulting time series have a small number of observations, e.g. annual data for the post-war period. Thus, a new detrending approach should have a version, which is directly applicable to those macroeconomic series.

In line with Hamilton (2018) and Mise et al. (2005), two-sided filters, like the HP approach, suffer from problems in real-time applications.[3] That is, the estimated components at the beginning and the end of the series are different to those in the middle part, because the filter uses observations from the past and the future to estimate the trend at a specific point in time. The same rationale applies, in accordance with Cogley (2008), to band-pass filters, where at the end of the sample period future values of the variable are not available. Furthermore, Gallegati et al. (2017) show in a comparison of the CFF and wavelet analysis that boundary points delivered by wavelet transforms also need to be interpreted cautiously. To solve this drawback auxiliary forecasting models are sometimes introduced to create unavailable future observations. Although this idea reduces errors at boundary points, it is a complex adjustment and relies on the introduction of an auxiliary forecasting model. As the proposed local polynomial trend estimation approach uses past and future observations in order to estimate the trend function, it also needs boundary correction. To address the criticism formulated by Hamilton (2018), an asymmetric boundary kernel is introduced into the local polynomial estimation approach and the bandwidth at the boundary is kept constant to provide robust estimators. Furthermore, the local polynomial estimation approach automatically corrects at those points, if $p - v$, the order of the polynomial minus the order of the derivative, is odd.

Although Luo and Startz (2014) argue in favor of a deterministic trend in US GDP data (except a break in 1973), the characteristic properties of this kind of macroeconomic series are not sufficiently examined. Perron and Wada (2009) obtain similar results and propose the use of a piecewise linear trend to allow for possible structural breaks. This means, the trend is deterministic, although a change in the slope of the trend function may be present. The ambiguity, whether the DGP is a deterministic function or a stochastic process is in accordance with Durlauf et al. (2005) also important for aspects concerning economic theory

[3] It is important to note that one-sided filters also have shortcomings, which are for example addressed in Metz (2011).

and policy implications. Phillips and Perron (1988) introduce a unit root test to distinguish whether data obey a unit root (are stochastic processes, difference-stationary, DS) or whether they return to a mean or trend level (trend-stationary, TS). Since the initial work of Phillips and Perron (1988) various unit root tests under numerous hypotheses were developed. Nevertheless, in accordance with Hansen and Racine (2018) numerous improvement possibilities are still present. For example, Metz (2011) infers that unit root tests have little power, when the DGP is nearly integrated. Furthermore, due to missing theoretical considerations, a unit root test under a nonparametric alternative does not exist. The lack of a unit root test requires the calculation of empirical test statistic values using a bootstrap method. Calculating empirical test statistic values allows one to detect unit roots and hence provides reliable estimates of trends and cycles. In other words, a reliable unit root test leads to an appropriate selection of either a model for deterministic or stochastic processes. Consequently, the obtained results do not suffer from spurious estimates or artifacts in the sense of Cogley and Nason (1995), Murray (2003) or Gallegati et al. (2017). Although the data-driven local polynomial trend estimator is developed for TS processes, it could be applied to DS processes. Therefore, an appropriate unit root test needs to be carried out for the residuals in a first step in order to clarify the characteristics of the underlying time series. In a second step, the local polynomial trend estimation is used for the original data in the TS case or the first differences of the data in the DS case. In this regard, the method is also able to handle both properties.

For parametric statistical inference it is common sense to test the estimated coefficients for their significance. However, testing in nonparametric estimation is in line with Calonico et al. (2018) more difficult due to the selection of an appropriate bandwidth. In order to test whether a particular section of the nonparametric trend is linear or significantly different from other episodes, this thesis introduces a graphical tool in the sense of Ferraro et al. (2010). In other words, the estimated time-varying coefficients are tested, e.g. against the constant coefficients of any parametric approach. Beyond, the test can be used to test any other detrending method against a local polynomial alternative in order to demonstrate that the choice of the approach and the subsequent assumptions crucially determines the outcome. In accordance with Hjellvik et al. (1998) and Calonico et al. (2018) confidence bounds for the nonparametric trend are calculated. In this vein, also the respective confidence interval (CI) for any derivative are constructed. Economically, the derivatives of the trend are also important for the estimation of growth rates. Hence, the bandwidth and the variance factor are used to calculate the confidence bounds of the trend function of the level data and the growth rates in order to test different trend specifications. Based on this bandwidth different hypotheses can be tested, e.g. the linearity of the trend and the time-dependence of the slope coefficient. Economically, this test provides information on possible (secular) changes in the trend function and indicates how, when and to what extent economic activity and economic conditions have changed over time.

1.2.2 Economic shortcomings

Although Mankiw et al. (1992) provide the point of departure for empirical growth analysis, many usually applied methods are in line with Canova (1998a) and Škare (2017) not linked to economic theory. This is demonstrated by Cogley (2008) for the simple linear trend, which treats every shock as neutral. Though this may be appropriate for monetary policy, other shocks like technical innovation (cars, steam engine, central heating) remain important in the long-run. Škare (2017) demand the development of a detrending approach that is relevant for economic interpretation and links theory and methodology. Within this argumentation, Zarnowitz and Ozyildirim (2006) argue that transitory business cycle fluctuations are not independent of long-run growth. Furthermore, they require a nonlinear or at least a local or piecewise linear function for the trend. Consequently, driving factors might have permanent and transitory effects, while permanent and transitory shocks need not be uncorrelated. Hence, the interaction between trend and cyclical movements is largely disregarded in the literature by the standard assumption of i.i.d. errors in the majority of detrending methods and needs to be taken into account. In other words, the dependence structure of the components is crucial and needs to be considered by cautious econometric modeling. In accordance with Schlittgen and Streitberg (2001), a time series can have three different dependence structures. Therefore, let Y_t be a stationary process with the autocovariance function γ_τ, $\gamma_0 > 0$, which has long-memory, when $\sum_{\tau=0}^{\infty} |\gamma_\tau| = \infty$. The process obeys short-memory, when $\sum_{\tau=0}^{\infty} |\gamma_\tau| < \infty$ and if $\sum_{\tau=0}^{\infty} |\gamma_\tau| = 0$, for $\tau \neq 0$, the process has antipersistence or no memory.

In this vein, it is important to relax the i.i.d. assumption and to allow for the possibility of dependent errors. This becomes obvious in Figure 1.3 a), where the autocorrelation function (ACF) of the LN-US GDP series from 1790 to 2017 is shown. The ACF displays a positive autocorrelation for the LN-US GDP data and demonstrates the nonstationarity of the series as the ACF does not decay exponentially to zero as the lag increases. Figures 1.3 b) and 1.3 c) show the ACFs for the detrended series using the LLR and the HP filter, respectively. Nevertheless, the ACF in Figure 1.3 a) decays slowly to zero as the lag increases and the allowance for short-memory seems an appropriate point of departure for the analysis of macroeconomic trend and cycle processes. This is confirmed in Figure 1.3 b) by the ACF of the standardized LN-US GDP series using the LLR. Adjusting the series by the long-term dynamics results in stationary data, confirmed by the ACF, which decays rapidly to zero at short lags. Moreover, since the theoretically suggested dependence of the components is considered in the short-term in a macroeconomic sense, the allowance for short-range dependence is straightforward.

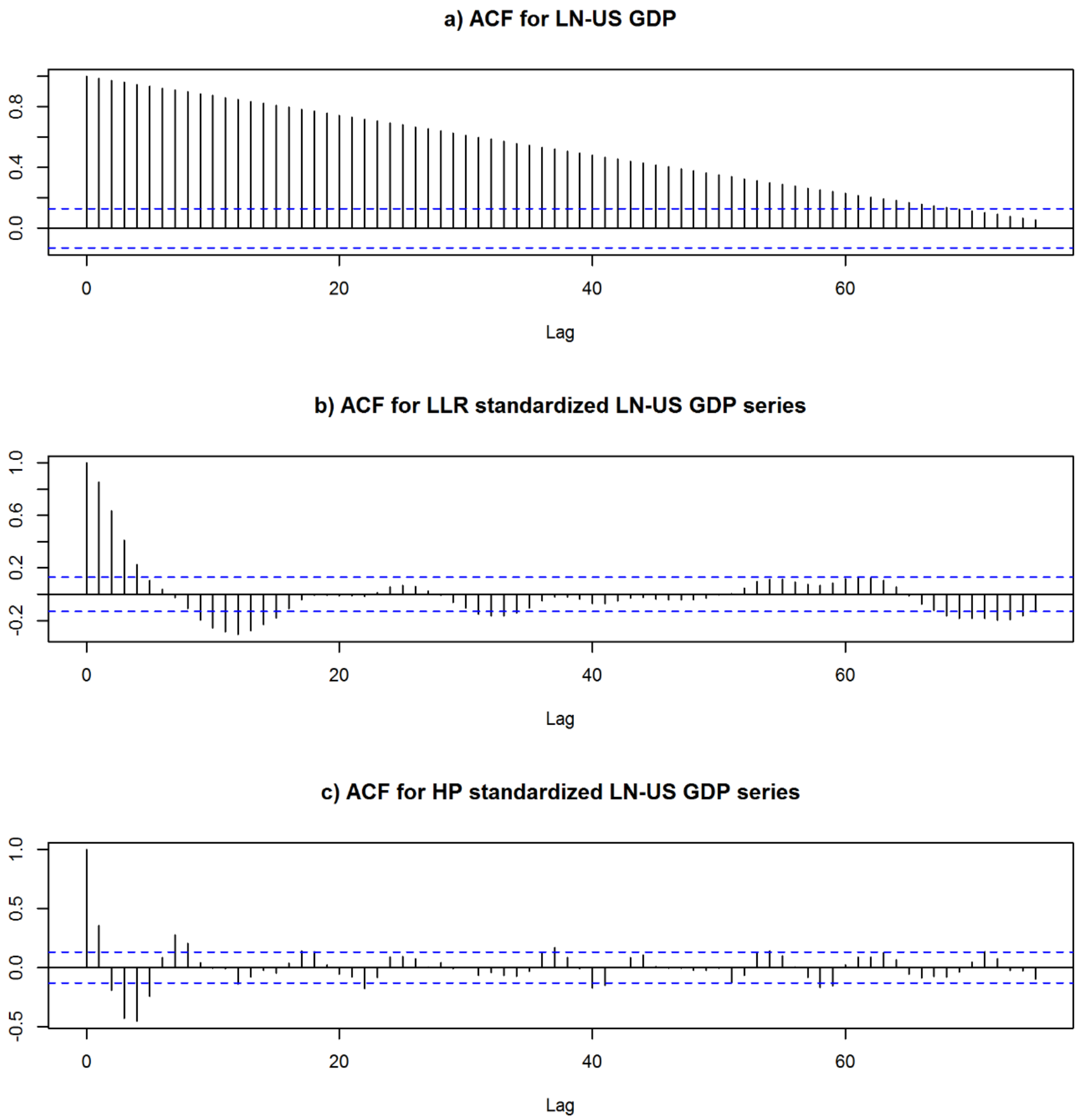

Figure 1.3: ACF for the observed and standardized LN-US GDP series

Notes: a) ACF for the original observed LN-US GDP series. b) ACF for the standardized LN-US GDP series using the LLR and c) ACF for the standardized LN-US GDP series using the HP filter with $\lambda = 6.25$.

Furthermore, the dependence structure delivers important information on the underlying growth process and the steady state adjustment. This fits into the well-known idea of log-linear growth processes with one steady state, e.g. proposed by Solow (1956) and others.

However, restricting the model by these neoclassical assumptions leads to possible bias. In other words, allowing for multiple steady states and possible nonlinearities, as mentioned in Durlauf et al. (2005), is a straightforward extension. This extension is modeled in endogenous growth theories, like the influential work of Jones (1995).

Moreover, this dependence structure is fully captured by the bandwidth, which represents the smoothing parameter in the proposed nonparametric estimation approach. Following Wynne and Koo (2000), the smoothing parameter, e.g. for the HP filter, has no economic intuitive interpretation. Since the dependence structure, displayed by the bandwidth, delivers information on the steady state adjustment, the length of the bandwidth is interpretable as the length of constant growth periods or steady states. Thus, a trend segment may be regarded as a stationary time range supporting the momentary growth trend. As noted by Morley and Piger (2012), this growth trend should include "steady state effects of the factors that drive long-run growth" (Morley and Piger, 2012, p. 210). In this sense the steady state is the level to which the process converges in the absence of future transitory or permanent innovations. In this manner, economically stationary growth periods in accordance with the underlying economic growth conditions of the respective period can be identified. Consequently, allowing for these expansions link growth and business cycle analysis more closely to economic theory.

Furthermore, the asymmetry of business cycles is a widely hypothesized but empirically not verified question. In accordance with Gallegati et al. (2017) this is partly due to identification problems of a small number of cycles within a given sample size. Among other data series, Razzak (2001) investigates the asymmetry in US GDP data finding no hints for asymmetry. Peiró (2004) draws the same conclusion on the non-existence of asymmetry for industrial production in seven European countries. In contrast, Sichel (1993) shows the presence of asymmetry over the business cycle. Perron and Wada (2009) demonstrate sharp downturns in recessions which display large variances whereas expansions occur as gradual increases. Also, Morley and Piger (2012) find hints in favor of asymmetry using standard and nonlinear time series models. Whereas linear models imply symmetric fluctuations, nonlinear models allow for asymmetric fluctuations away from the trend. However, Morley and Piger (2012) show that due to parsimonious model selection, the AR models are already a suitable choice for the underlying data and are more appropriate than other model specifications. Moreover, the authors suggest that the model specification is crucial for the analysis of asymmetry over the business cycle and no generalized method exists. This is also obvious from Figure 1.2, where the simplest measure of asymmetry, namely the number of peaks and troughs, vary greatly among different approaches. The potential existence of asymmetry, calling for more cautious analysis, e.g. by means of a more general, data-driven trend and cycle estimation procedure.

In addition, heterogeneity in the business cycle and the subsequent growth component depending on the country under investigation is a possible feature. Durlauf et al. (2005) argue against constant parameters across different countries due to heterogeneity, complexity and historical experiences. Thus, each country moves towards its “own different steady-state growth path” (Durlauf et al., 2005, p. 578) and multivariate analysis, like the VAR model, may be misleading. In the same vein, Greiner et al. (2016) affirm the advantage of time series approaches, which do not restrict growth to be the same at all times across all countries. Therefore, the time series analysis of each country separately seems a logical starting point.

Another open debate in the existing research on dynamic growth processes concerns the possibility of a secular decline in economic growth. Thus, the analysis of the current development of trend dynamics is an important topic, which represents the transition phase towards forecasting growth processes. Since the reintroduction of the term secular stagnation by Summers (2014), many empirical as well as theoretical studies analyze the decline in growth. Gordon (2015) stresses the importance of growth dynamics arguing that “secular stagnation is evident in every measure of economic performance over the past five years, most notably the growth rates of output, labor productivity, and aggregate hours of work […]” (Gordon, 2015, p. 58). However, besides Jorgenson and Timmer (2011) and Kirwin and Mathy (2017) many studies focus on the theoretical considerations behind a systematic saving and investment mismatch at the zero lower bound without providing statistical firm confirmation. This evidence for significant changes in the slope of the long-term trend is usually indicated by the presence of structural breaks. Gallegati et al. (2017) summarize commonly used test methods and argue for the importance of such a structural one-time change when considering secular movements. Although, Fernald et al. (2017) use those breakpoint tests for the detection of a secular decline, they fail to detect any break since 2007. In accordance with Metz (2011) and Luo and Startz (2014), the explicit timing of such structural breaks is even more challenging. According to Perron and Wada (2009) the reason is that most breaks occur smoothly and no break test is able to capture smooth changes appropriately.

Furthermore, contradicting arguments by Mokyr (2014) as well as Brynjolfsson and McAfee (2014) point towards the third industrial revolution and the possibilities of technological innovations. These improvements of digital efficiency will become transformative in the next years and further enhance future benefits and consequently growth. In other words, digital advances, big data, robotics and artificial intelligence are able to counteract a possible stagnation. These pessimistic and optimistic arguments have a lack of statistical firm confirmation and hence lead to quite different scenarios for the future of growth. Since secular stagnation is a phenomenon observed at the current state of the economy, it is methodologically related to the estimation quality at time series endpoints. Furthermore, it is linked to the estimation of trends in level data and growth rates and their alteration. Thus, the possibility of a decline is closely related to the disadvantages of well-known trend estimation methods at boundary points and the development of a test for a secular decline. As indicated in the previous subsection, the introduction of a test based on the nonparametric trend estimation may shed further light on the evidence of secular stagnation. This is in line with Calonico et al. (2018), since inference on nonparametric methods is more robust compared to a possible parametric misspecification. Therefore, nonparametric inference can be a starting point for more accurate policy implications beyond unconventional monetary policy.

Furthermore, the precise estimation at boundary points eases the real-time analysis of the output gap, which goes hand in hand with the secular stagnation hypothesis and the business cycle analysis. Orphanides and van Norden (2002) demonstrate that the main determinant of revisions in the output gap, which could be seen as the difference between trend and cyclical component, is the boundary problem of most detrending methods. Surprisingly, multivariate methods, which include inflation, unemployment and interest rates, cannot improve the results based on univariate time series models. Thus, the output gap estimation has large influence on real-time policy decisions concerning for example the correct economic stabilization policy. In contrast, a mismeasurement of the output trend at the boundary of the series can cause instable policy recommendations. Gerlach and Smets (1999) stress the importance of the output gap in transmission mechanics and in guiding ECB policies, due to its influences on future inflation. In addition, Álvarez and Gómez-Loscos (2018) report how central banks use the output gap in a Taylor rule for setting the interest rate. Hence, the improvement of estimation at boundary points is of increasing importance, especially since new elements, including the financial markets, arise (Borio et al., 2016).

1.3 Structure of this thesis and outlook

In order to improve prevailing methodological and economic shortcomings and to enhance the understanding of growth and business cycle dynamics, two theoretical and two empirical studies are presented in the following chapters of this doctoral thesis.

Chapter 2, *Data-Driven Local Polynomial for the Trend and its Derivatives in Economic Time Series*, presents joint work with Yuanhua Feng and Thomas Gries. It is a slightly adjusted version of a paper that is published as a working paper in *Paderborn University, Working Paper Dissertations No. 50/2019-06.* This contribution introduces the idea of a two-step fitting procedure, based on the decomposition of a time series into a deterministic and a stochastic component. In order to estimate the smooth, deterministic trend function nonparametrically, a data-driven local polynomial estimation approach is introduced. Within this local polynomial estimation approach the bandwidth is selected automatically with a data-driven IPI algorithm. The theoretical properties of that IPI algorithm for estimating the bandwidth endogenously are presented. The paper discusses the theoretical and practical performance of the IPI algorithm, considering several factors. In addition, the estimation of any derivative of the trend function and a nonparametric method for estimating the variance factor are introduced. The advantages of the local polynomial estimation and the IPI algorithm are demonstrated in a simulation study and two practical examples. These examples use quarterly US GDP from 1947.1 to 2016.1 and quarterly United Kingdom (UK) GDP data from 1955.1 to 2016.1. The paper provides the R package called smoots (smoothing time series), implements the IPI algorithm and makes it publicly available.

Chapter 3, *Data-Driven Local Polynomial Trend Estimation for Economic Data – Steady State Adjusting Trends* (single-authored) is published in a virtually identical version in *Paderborn University, Working Paper Dissertations No. 49/2019-05.* The paper examines the quality of the data-driven local polynomial trends, using local linear and local cubic polynomials, and the IPI algorithm in an extensive simulation study comprising TS and DS processes. It considers different bandwidth influencing factors that have an impact on the algorithm, like the order of the kernel function or the choice of the inflation factors, and explains how to select them in an economically and statistically optimal way. Moreover, it provides a detailed manual for applied macroeconomists and links the methodological advantages to macroeconomic log-linear steady state growth theories. Using the provided manual an application to real data and a comparison to the BW filter (Harvey and Trimbur, 2003) as well as the linear trend is carried out. Therefore, the aim of the paper is to demonstrate the wide application possibilities, the connection to macroeconomic theory and to replace other detrending methods by an enhanced alternative, while encouraging the use of the local linear regression in the field of economics.

Chapter 4, *Growth Trends and Systematic Patterns of Booms and Busts – Testing 200 Years of Business Cycle Dynamics* is joint work with Yuanhua Feng and Thomas Gries. An almost identical version of it is published in the *Oxford Bulletin of Economics and Statistics, 81*(1), 62-78. This study demonstrates an economic application of the local linear regression with respect to the further analysis of the remaining cyclical component. In accordance with Morley and Piger (2012) the estimated business cycle depends on the detrending method. The literature is extended using a fully data-driven approach without any assumptions on the functional form of the smooth trend function and by allowing trend and cycle to interact and not to be independent of each other. In a first step, the IPI algorithm is used to estimate the trend function, using a polynomial of order one. This yields a bandwidth of 54 years, which reflects the trend-supporting period. Further, a unit root test based on empirical test statistic values verifies the use of a nonparametric regression with stationary errors. Afterwards, the estimated trend function is tested for its nonlinearity. In a second step the original data are standardized by this trend and the cyclical component is obtained and further analyzed. Using the improved results for the cycle, a SETAR model is fitted to the cyclical component. Introducing this semi-SETAR model and fitting it to an unique long-term US GDP data set from 1790 to 2015 clarifies the discussion on the possibility of asymmetric business cycles. The results demonstrate a deterministic structure in the high regime and a more stochastic structure in the low regime. Hence, asymmetric business cycles exist, in the sense that deterministic expansions are more gradual than stochastic and deep recessions, which happen suddenly. In accordance with Sichel (1993) steepness and deepness types of asymmetry and time-irreversibility are detected.

Chapter 5, *Secular Stagnation? Is there Statistical Evidence for an Unprecedented, Systematic Decline in Growth?* is joint work with Yuanhua Feng and Thomas Gries. It is a slightly revised and extended version of a paper that is published in *Economics Letters, 181, 47-50*. This study provides statistical firm evidence for the secular stagnation hypothesis. This contribution applies the local linear regression and the test procedure for statistical inference based on nonparametric regression directly to the controversial discussed issue of secular stagnation. In accordance with Hansen (1939), secular stagnation is defined as “sick recoveries which die in their infancy and depressions which feed on themselves and leave a hard and seemingly immovable core of unemployment” (Hansen, 1939, p. 4). Summers (2014) reintroduces the terminology in the context of a systematic saving-investment mismatch, whereas Gordon (2012, 2015) focuses more on the supply side. However, the consensus among all explanations is that the result is a slowdown of GDP growth rates. Missing statistical evidence for a slowdown in growth trends, the study provides significant evidence for a persistent declining pattern in quarterly US GDP data from 1947.1 to 2018.2, annual US labor productivity (LP) from 1950 to 2018 and annual US multi-factor productivity (MFP) data from 1948 to 2017. That is, confidence intervals for the local linear trends in level data and growth rates are derived and compared to the linear trend and the constant slope, respectively. Moreover, the paper compares the dynamic growth patterns during the Great Depression and the Great Recession and demonstrates that the starting point of an unprecedented secular stagnation could be dated back to the burst of the dot-com bubble in 2000. Furthermore, in accordance with Summers (2014) and Gordon (2012), the paper investigates several variables as possible explanations of secular stagnation.

Chapter 6, *Concluding Remarks*, summarizes the findings of this doctoral thesis and discusses the methodological and economic implications. It additionally provides consequences for macroeconomic policy making. Furthermore, numerous application possibilities are shown that are not restricted to economic research topics. Moreover, a brief outlook for future research, for example concerning the finance-growth nexus, is given.

The empirical analyses throughout this thesis are carried out with R and the following packages: *fUnitRoots* (Wuertz, 2013) and *urca* (Pfaff et al., 2016) in order to test for possible unit roots in the data. *mFilter* (Balcilar, 2015) is used for estimating the HP filter and other detrending methods used for comparison. *moments* (Komsta, 2015) is applied for implementing the test of asymmetry from Sichel (1993). *bcp* (Wang et al., 2018) and *strucchange* (Zeileis et al., 2015) are used for the estimation of structural breaks. *tsDyn* (Di Narzo et al., 2016) and *tsseries* (Trapletti et al., 2017) are used for estimating AR, ARMA and SETAR models as well as for testing those models.

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