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Business Cycles and Institutions: Empirical Analysis

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Preface

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Overview of articles

The first article, Geloso and Kufenko (2015), replicated[1] in Chapter 2, was written together[2] with Vincent Geloso, PhD. in Economic History, London School of Economics and Political Science. The working paper version of the article was created in December 2014 after collecting feedback. The draft of the paper was presented on 17th December 2014 during the research seminar “Money, Employment and Growth”, at the University of Hohenheim. Afterwards it was submitted to the *Journal of Population Research*. The article was submitted on 23 February, 2015 and published on the 26 November, 2015.

[1] With a change made to the citation of the works of Serge Courville in Section 2.3.
[2] The contribution of the author to this article includes data preparation, descriptive analysis, stationarity and cointegration tests, structural break tests, detrending the series using filtering and differencing, designing and implementing vector autoregression analysis with exogenous control variables, conducting Granger-causality and white noise tests, validating the results for first differences and describing the results in detail.

Geloso, V. and Kufenko, V. (2015). Malthusian pressures: empirical evidence from a frontier economy. *Journal of Population Research*, 32(3):263–283.

The second article Kufenko and Geiger (2016), replicated in Chapter 3 with minor alterations[3], was written together[4] with Dr. Niels Geiger, University of Hohenheim. The working paper version of the article was created in July 2015 after two rounds of presentations. The draft of the paper was presented on the 29th April 2015 during the research seminar "Money, Employment and Growth", at the University of Hohenheim, and at the 19th Annual ESHET Conference on "Great Controversies in Economics", 14-16 May 2015 in Rome, at the Roma Tre University. After processing the feedback it was submitted to *Scientometrics*. The article was submitted on 25 June 2015 and published on 9 February 2016.

Kufenko, V. and Geiger, N. (2016). Business cycles in the economy and in economics: an econometric analysis. *Scientometrics*, 107(1):43–69.

The third article in a form of a working paper, Kufenko (2016), replicated in Chapter 4 with minor alterations, was written solely by the author. The draft of the working paper was made available online in February 2016 and was presented at an international conference "Cliometrics and Complexity" during 9-10 June 2016, in Lyon, at the Ecole Normale Supérieure de Lyon. After processing the feedback, it was submitted to a peer-reviewed journal *Journal of Business Cycle Research.*

Kufenko, V. (2016). Spurious periodicities in cliometric series: simultaneous testing. Violette Reihe Arbeitspapiere 48/2016, Promotionsschwerpunkt "Globalisierung und Beschaeftigung".

[3] Citations were modified to adhere to the overall citation style. Changes had been made in coloring schemes of Figures 3.1 and 3.2 in order to preserve the overall style of the thesis. The indication of the exact version of the "FCVAR" Matlab package (1.3.2), used in the article, was specified. In Section 3.3.2 full names of information criteria is given together with abbreviations for consistent representation. The misplaced values '5' and '2' in the last two rows in column 'Economics' of Table 3.9 were corrected accordingly.

[4] The contribution of the author to this article includes data preparation, descriptive analysis, stationarity, cointegration and fractional cointegration tests, detrending the series using filtering, designing and implementing vector auto regression and fractionally cointegrated vector autoregressive models, conducting Granger-causality, long-run exogeneity, Diebold–Mariano and white noise tests and describing the results in detail.

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General Introduction

In the Introduction the motivation and the overall conceptual framework of the dissertation is presented. In addition, the background of each research question for each chapter is formulated in brief, as well as the interlinks between the chapters. The goal of this section is to highlight the main economic debates and issues relevant for the dissertation, emphasize the key research questions, and therefore the research agenda of the dissertation, provide brief background for each chapter and show the relations between them.

1.1 Introduction and motivation

The motivation of any research consists of several layers. In order to provide a structure for the motivation behind the given work, it is needed to distinguish between the motivation for the choice of the research field of the author, selection of the topic and the motivation behind each chapter. Without engaging in a long preamble, one has to highlight intrinsic motivation, as well as debates in the *state-of-the-art* research, to which the author intends to contribute.

After conducting empirical research on the topics of economic growth and inequality (Hagemann and Kufenko, 2016; Kufenko, 2015), the author intended to continue empirical work, yet, extending it to other fields: business cycle research and cliometrics. Both fields offer fruitful grounds for applications of the well-established as well as relatively new methods to novel datasets. The arsenal of empirical tools for business cycle research is very diverse and among other methods, includes detrending methods, causal inference and frequency analysis. However, with all the variety of tools available, a careful and diligent application of these is necessary, with full awareness of specific features related. As an example, the problem of detrending and the emergence of spurious periodicities can be given. The latter may be related to measurement errors or, which is more relevant for this work, specific features of empirical tools applied. Through rigorous testing and cross validation, one could minimize spuriousity, yet it is unlikely to rule it out completely. The research in the field of cliometrics has been gathering pace during the recent years and covers a variety of topics (for details see Diebolt and Haupert, 2015). Among these are historical and institutional regimes and economic cycles. Cliometric research allows to quantitatively analyse history and better understand institutional arrangements. Therefore, the marriage of diligent and cautious empirical analysis and cliometrics is piercing through the chapters of this work. Having considered the reasoning behind the choice of the research direction, let us now proceed to ideas behind the topics.

As it follows from the dissertation title, its topic is *business cycles and institutions: empirical analysis*. The motivation behind the choice of that topic is threefold.

Firstly, with regards to the given work, regularities are cyclical fluctuations, existing in a certain regime, which can represent a set of constraints. Once the regime changes, the magnitude, phase and periodicity of the cycles may also change. Moreover, certain cycles may vanish or the relation between cyclical fluctuations of different variables may change. Bearing Crafts and Mills (2009) and Acemoglu et al. (2005) in mind, significant changes in the regime due to gradual Smithian growth process or due to cumulative institutional changes, can result in changes in certain economic regularities or lead to their disappearance. One of the vivid examples are the Malthusian cycles, also known as the Malthusian checks[1]: the positive check (positive relation between prices and mortality rates) and the preventive check (inverse relation between the prices and the fertility rate). In different countries demographic transition and the escape from the Malthusian cycles took place at different times (Reher, 2004). Therefore, the change of economic regularities due to transition from one regime to another (Acemoglu et al., 2005; Crafts and Mills, 2009; Reher, 2004) is the main motivation for the given topic. The role of institutions in this transition is still subject of debates; however, in this work we will discuss which institutions could be responsible for a Malthusian trap and how the transition could occur. Secondly, the empirical analysis of the existing economic regularities is also worth consideration, yet one has to make a novel contribution. The focus on business cycles allows us to broaden the range of potential research questions. One of the central statement on the far reaching effects of business cycles can be summarized by the statements made by Mills (1868) and Fabian (1989), whose observation suggested that economic cycles were to a large extent fuelling developments in economic thought. One usually approaches economic regularities in a deductive way: a theory guides us through complex relations between variables and their fluctuations. Yet, theories and models are created by economists, who

[1] Here we assume that prices are a proxy for real wage variation, since nominal wages were relatively stable (see Chapter 2, Section 2.4).

often reflect the contemporary reality. If ”panics produce texts”, then economic crises and downturns in business cycles can potentially induce the feedback from economic theory in terms of new research output. Therefore, the economic history of business cycles and history of economic thought are the motivation behind the given topic. Bibliometrics is a reletively young field and offers news quantitative insights in the developments in economic thought (see the example of Geiger, 2014, related to behavioral economics). Needless to say, the scarcity of empirical works on the interaction between business cycles and bibliometric variables offers additional motivation to engage in this relatively new research direction.

Thirdly, there exists motivation, driven by the known caveats of the tools, used for business cycle analysis. The crucial object of empirical analysis in this case are the cyclical fluctuations: Zarnowitz (1992) notes that it is crucial to correctly identify the secular trend and extract the cyclical component. Although this task may appear straightforward, in fact, it contains certain caveats, which may lead to the emergence of spurious periodicities and therefore, spurious research findings, regardless of the research question. Coupled with the well-known Slutzky–Yule effect, related to formation of regularities from series of random shocks (for details see Slutzky, 1927, 1937; Yule, 1927), the emergence of spurious periodicities can be related to detrending procedures. In particular, detrending, depending on the method, can amplify the power of certain frequency ranges. The significance testing for periodicities has been addressed by Thomson (1982) and Mann and Lees (1996), whereas the latter issue has been considered in detail by Nelson and Kang (1981); Pollock (2013, 2014) and briefly by Woitek (1997). Nevertheless, the issue of spurious periodicities remains a relevant debate. Spurious shifts in spectral density related to methodological features of detrending tools, in fact, deserve much more attention. Since the author had planned to write an article on methodological caveats, he applied different methods for filtering, estimation and cross validation (e.g., filtered against first differenced data in Chapter 2 and filtered against fractionally differenced data in Chapter 3). The motivation behind the latter topic of detection of spurious results expands beyond the frames of the given work and will manifest itself in further research of the author. In order to be more specific, it is necessary to highlight the motivation behind each chapter. Bearing in mind a number of works on the Malthusian checks in Europe (see Crafts and Mills, 2009; Fertig and Pfister, 2012; Galloway, 1988; Nicolini, 2007), and very few works on these effects in the new world (see Haines, 2000). One of the distinctive feature of frontier economies is a relatively high land-to-labour ratio (Álvarez Nogal and Escosura, 2013). Even if we consider heterogeneous land quality, the severity of the constraints on availability[2] of land, which are underlying to the Malthusian

[2] Some authors disagree on this issue (see Greer, 1985; Ouellet, 1972, 1980; Russell, 2012) and we elaborate on the related debates in Chapter 2, Section 2.3.

cycles, in frontier economies is unlikely. Yet, institutional arrangement which limit the availability of land, even in case of its abundance, may pose a constraint. Therefore, the first question to be asked is *whether the Malthusian effects could be present in a frontier economy and which institutions could be responsible for the Malthusian regime and the transition from it?* This question is answered in Chapter 2: where we analyze the Malthusian regularities and show how they dissolve with a number of economic and institutional changes. The next research question is to empirically test the statement "panics produce texts" of Fabian (1989) and therefore to ask *whether there exists an econometric evidence for the statement that "panics produce texts"?* If economics as a science reacts to economic fluctuations in terms of research output, how can we measure this feedback and what is the magnitude of this response? In order to approach the issue in a quantitative manner we build up our bibliometric analysis on the work of Besomi (2011), who identified the keywords in the economic literature related to the phases of business cycle. This allows us to derive bibliometric variables and perform inference on their interaction with economic ones. This research question is addressed in detail in Chapter 3. The last question to be asked is *how can spurious periodicities emerge and how could one test for these?* The latter question concerns the reliability of detrending methods – the main tools used in business cycle empirics in order to extract the trend and cyclical components. Estimation methods may yield spurious results if the spectral density of the cyclical fluctuations is altered during the detrending process. In particular, one of the main research questions in business cycle research is the duration of cycles (see Cendejas et al., 2015; Diebolt, 2014; Metz, 2011). If detrending methods can create spurious periodocities, (as mentioned in Pollock, 2013, 2014; Woitek, 1997), how will the estimation of the spectral density be affected and whether it is possible to test for such spurious periodicities. This question is dealt with in Chapter 4 by the means of simultaneous significance testing of spectral density peaks of different types of signals.

Let us proceed to a more specific consideration of the background for the chapters of the dissertation.

1.1.1 Business cycles and institutions: escaping from the Malthusian cycles

A brief introduction to the Malthusian cycles is needed, in order to understand the role of Chapter 2 in the dissertation. There are two important aspects: first of all, one has to define the Malthusian cycle and the economic and institutional framework related to it – here an example of a frontier economy, like seventeenth – nineteenth century Canada, is illustrative; the second aspect, it the dissolution of the Malthusian cycles, and the factors, which could have led to this change.

There are a number of empirical works on the Malthusian effects on European countries and a reiteration of literature overview from Chapter 2 is unnecessary. Yet, at this point we should focus the idea of the Malthusian cycles. Perhaps one of the most illustrative works on the Malthusian effects are Kelly and Ó Gráda (2014), Campbell (2010), Nicolini (2007) and Crafts and Mills (2009). Recently few works emerged, where the emphasis is put to institutional constraints, rather than physical constraints on land (e.g. Guinnane and Ogilvie, 2008). In the context of frontier economies and high land-to-labour ratio, as mentioned before, such institutional constraints are of particular interest: they may have the same implications as the physical constraints on land. The essence of the above-mentioned works can be summarized in the following way: limited availability of land leads to constraints for population growth and a result the positive and preventive checks emerge (see Foreman-Peck, 2016, pp. 242–249). The positive check is related to an positive relation between prices and death rates (or an inverse relation between real wages and death rates), whereas the preventive check is related to an inverse relation between prices and birth rates (or a positive relation between real wages and birth rates)[3]. Malthusian effects are formed from two types of cycles: the population cycle and the price cycle (Commons et al., 1922, pp. 244–245): the population cycle represents oscillations in the equation between population and natural resources and the Malthusian business cycle represents oscillations of demand and supply. Another important feature of the Malthusian cycles is the semantics behind the demand: for Malthus, demand and supply were related to consumption and production, and higher prices would be associated with scarcity (e.g., due to a supply shock) rather than competition.[4] Bearing the positive check in mind, one could say, that is a Malthusian regime, the fluctuations in prices could be deadly. Therefore, an empirical investigation of the presence of the Malthusian effects would require a system of equations, containing an equation for prices (or real wages), death rates and birth rates and causal inference, based on this system. Alternatively, one could use nuptiality (as in Galloway, 1988) instead of the birth rates, or complimentary. The Malthusian regime is to a large extent determined by the constraints imposed on an economy and population. However, looking at the new frontier economies, the abundance of land should not be an issue: physically, there is sufficient amount of land to cultivate, even bearing in mind land quality of climatic zones. Yet, it is the amount of cultivated land which plays the decisive role – here institutional arrangements and land law can play an important role. This idea is elaborated in Chapter 2 with the focus on the transition from the French laws to the British ones after the conquest of Quebec in 1760. An example of such institutional transition, is the abolishment of seigneurial tenure after

[3] For more details see Persson and Sharp (2015, p. 54)

[4] For detailed discussion of the theories of value of Ricardo and Malthus see Commons et al. (1922).

1791: the regime which governed settlement of farmers and their attachment to the cultivated land. The concept of the Malthusian cycles is easy to grasp, however, one should not consider it as a permanent state of the economy: as Galor (2005); Galor and Weil (2000) notes, eventually countries escaped the Malthusian stagnation and economic growth started to pick up. Moreover, the accompanying demographic transition involved many aspects including longevity (Cervellati and Sunde, 2015) and height increase (Dalgaard and Strulik, 2016; Schneider, 1996). Yet, the timing of this transition was different for each country. A more challenging and complicated task, comparing to the analysis of the Malthusian cycles, is, therefore, to capture this transition. For this task, one could test for structural breaks in the data and create sub-samples or one could use estimations with a rolling window (see Chapter 2 for details). First strategy would account for influential institutional changes, whereas the second strategy would capture gradual changes due to Smithian growth or market integration. As we will see in Chapter 2, although that the structural break in prices data occurs very soon after the British conquest of Quebec, there was a gradual decrease in volatility of the key variables and evidence of market integration (decrease of the volatility of the spreads between regional prices). Chapter 2 is not focused solely on Malthusian regularities, but rather on the escape from the Malthusian stagnation and on the role, which the institutional arrangements, among other factors, could play in this transition. An important note has to be made on the methodological aspects for this chapter: bearing in mind that Chapter 4 analyzes the problem of the emergence of spurious periodicities after filtering, in Chapter 2, filtering and differencing are both used for cross-validation of the results. The transition from the Malthusian regime involved separation of the population cycles from the economic cycles: the latter ones remained in the focus of further chapters. In the given chapter we treat regularities as multivariate and dynamic, in the sense, that we assume that the characteristics of these regularities may change through out time. The next chapter focuses on a different topic: a particular investigation of the impact of economic regularities on regularities in economics as a science. In addition, in Chapter 3 we expand the empirical analysis of business cycles from the short run to the long-run dynamics, by including the long memory effects in the empirical framework.

1.1.2 Business cycles and science: are economic cycles and cycles in economics related?

In Chapter 3 the statement that "panics produce texts" of Fabian (1989) is analysed quantitatively and in two time dimensions: the short run and the long run. The time frames of the analysis cover the period from the end of the nineteenth century to 2012 for most of the series. As noted before, Chapter 4 is focused on caveats of detrending, therefore, along with the standard vector autoregressions

(VAR) for the short run analysis of the cycles obtained with the Kalman filter, we also apply fractionally cointegrated vector autoregressions (FCVAR), in order to capture long memory effects and avoid filtering. In regards to methodological apsects, the works of Johansen (2008); Johansen and Nielsen (2012); Jones et al. (2014) provided strong motivation for the choice of the FCVAR framework. The FCVAR analysis is a necessary mean of validation, since the Kalman filter may be also prone to spurious periodicities (Nelson, 1988). One has to note that scientific research has its own production function and constraints (see Ramos et al., 2007; Spangenberg et al., 1990). Previously, most attention has been paid to endogenous determinants of the research output (human capital, tenure, communication and many others, as in Spangenberg et al., 1990, p. 253). In Chapter 3 we focus on exogenous determinants of scientific output in economics: the influence of cyclical fluctuations in economic variables. The first substantial empirical work on quantifying the bibliometric data from the field of economics was performed by Besomi (2011), who suggested a list of words, most frequently used to describe the phases of economic cycles. His work was continued and the bibliometric data was collected based on the given list. The analysis performed in Chapter 3 goes beyond the "panics produce texts" statements and tests three directions of potential causality: from economic cycles to cycles in bibliometric data; the simultaneous causality and the direction from the bibliometric data to economic cycles. The notion 'causality', as in Diebold (2008, p. 230), is related to predictive causality, rather than economic causality. Moreover, the given notion is twofold: concerning the VAR analysis, it relates to the Granger-causality test; whereas, concerning the FCVAR analysis it is related to the long-run exogeneity test. This duality allows us to cover the short run and the long-run interactions between the economic fluctuations and the fluctuations in scientific output.

A separate remark has to be made on the long memory effects in the context of business cycle empirics. It is often the case that economics as well as econometrics profit from scientific spillovers from other sciences: the concept of long memory effects migrated to economics from natural sciences, in particular hydrology (Hurst, 1951, 1957; Mandelbrot and Wallis, 1968). However, the long memory concept was introduced to the problems of economics and business cycles with a certain lag. One of the first works of this kind were Mandelbrot and Van Ness (1968) and Mandelbrot (1972): whereas in the first work a small remark was made on the existence of the long memory effect in economic series, the latter work was solely focused on economic application. The details on the long memory effects and related tests are also provided in Chapter 4; however, to ensure a smooth transition a brief background information is needed. Long memory arises in case of long-run irregular fluctuations with large amplitudes. A simple illustration of a persistent process as in Mandelbrot and Van Ness (1989, p. 30) and Baillie (1996, pp. 10–14) is self-explanatory and can be summarized as follows. In the long memory theory d, the fractional difference operator, plays an important role: The long memory effect is present if $0 < d < 0.5$, which means that is has positive autocorrelation coefficient, decreasing at a hyperbolic rate. If $-0.5 < d < 0$, then short memory is assumed. Whilst $d = 1$ corresponds to a unit root case (Phillips, 2007, p. 105), as Baillie (1996, p. 22) notes, for $0.5 < d < 1$, the process will not be covariance stationary, however, still mean reverting (will not contain a unit root), and in such series the existence of fluctuations and irregularities in the long run is also possible. This issue is elaborated in Section 5.2.3 of the discussion. Therefore, a long memory process of a fractional order is a process neither $I(0)$ nor $I(1)$. This concept will be revisited in Chapter 4 in relation to spectral analysis of business cycles, in the context of estimating the differencing parameter $\hat{d}$. As for Chapter 3, fractional differencing is used for the FCVAR analysis, therefore, allowing us to capture long memory effects in the interaction between the economic and bibliometric variables.

In the last chapter the focus is moved from the multivariate analysis to the univariate analysis of the time and frequency domains and focus on methodological problems of detrending, and in particular, on the emergence of spurious periodicities. This methodological problem is the reason behind the cross-validation of the results by running the estimation on filtered and differenced series (Chapter 2) and by including models allowing for fractional cointegration and fractional differencing (Chapter 3).

1.1.3 The methodology of business cycles: spurious periodicities

The Slutzky–Yule effect, mentioned before, is not the only caveat in the empirical analysis of business cycles; however, shifts and distortions in the spectral density of economic fluctuations may have far reaching implications for the end results and any inference, no matter what the research question is. One of the most fascinating and yet challenging tasks in the empirical business cycle analysis in the inference about the periodicity of fluctuations. The empirical strategy for this question differs from one study to another, but certain common points are inevitable: outlier adjustment, detrending and frequency domain analysis. As for the outliers, different methods of detection exist (see discussion in Metz, 2011) and for frequency domain analysis the most wide spread[5] methods are spectral (e.g. Diebolt and Doliger, 2008) or wavelet analysis (e.g. Gallegati and Semmler, 2014, pp. 52–70). In Chapter 4 spectral analysis is applied, since the estimation of spectral density using wavelets is not straightforward (see Tabaru and Shin, 2003).

The frequency analysis of business cycles is of particular interest also because of the typical spectral density shape of economic variables, which exhibit peaks at

[5] For application of non-linear tools, including the concepts from the chaos theory see Kelsey (1988).

low frequencies in the vicinity of zero (Granger, 1966). In Chapter 4 different types of cycles (including the ones with very low frequencies), their periodicities and the methods, which were used to obtain them, are discussed in detail: different data and time frames, adjustment and detrending procedures, as well as identification strategies for the dominant frequency can produce different results. Therefore, the results of spectral analysis are exposed to methodological heterogeneity and related caveats.

Let us focus on the problem of spurious periodicities. Cooley and Prescott (1995, pp. 27–29) provide an example of detrending with the Hodrick–Prescott filter using the smoothing parameter $\lambda = 1600$ for quarterly and 100 for annual data. This value would eliminate fluctuations with periodicity longer than eight years. Cooley and Prescott (1995) note that filtering bands can be set to approximate the duration of business cycles between three and five years, which appeared to be plausible for the authors. Almost a decade later Ravn and Uhlig (2002) proposed the value of 6.25 for the annual data which roughly corresponded to the upper bound of eight years. The latter work with the rule of thumb smoothing parameter had been quoted numerous times[6] and could potentially become a *self-fulfilling* prophecy (see Merton, 1948), or a self-sustaining institution: if one limits the upper bound of cycles up to eight years most likely the desired effect will be obtained. Pollock (2013, 2014) notes, the spurious peaks in the spectral density may emerge in the vicinity of the cut-off band. Coupled with the Slutzky–Yule effect this amplifies the risk of spurious filtering results. One may resort to first differences as a method of detrending, yet this would be a bold conclusion: Cooley and Prescott (1995, p. 28) note the filtering suppresses the frequencies outside of the bands and amplifies the ones inside; whereas, differencing[7] suppresses only the lower frequencies and amplifies the higher ones. The latter statement also revisits the issue mentioned in Nelson and Kang (1981, p. 750), yet the claim of these authors was that even a randomly generated process, if inappropriately detrended, would exhibit spurious periodicities. The notion of ‘inappropriate’ detrending is rather vaguely defined and does not relate to the usage of statistical filters, but rather to isolating the trend with a regression on time. A complimentary, but more specific statement was made by Pollock (2013, p. 113), who wrote that differencing suppresses lower frequencies and amplifies higher frequencies and filtering, in particular if the summation operator is involved, gives unbounded power to lower frequencies in the vicinity of zero. Pollock is being more specific about the spectral distortions, which can be caused by filtering. As for the implications for the empirical analysis of the business cycles and their duration, the problem of spurious

[6] As of 20th August 2016, the *Review of Economics and Statistics* reported at least 336 citations in of the given work in other publications.

[7] Often referred to as the ‘first-difference filter’. In Chapter 4 the word ‘filter’ is not used together with ’differencing’ in order to avoid confusion. The word ’filter’ denotes a statistical tool.

periodicities is extremely important: when using a moving average or a more sophisticated tool to filter the series, one may obtain spectral density peaks at lower periodicities; whereas, when using first differencing, the long memory information, as well as the information on long periodicities may be lost and, most likely, the spectral density peaks will be at higher frequencies. Chapter 4 is focused on testing for such methodologically related spurious periodicities. After adjusting for outliers and estimating the differencing parameter, two types of signals using a filter and using differencing are derived. As done in Mann and Lees (1996), the appropriate benchmark model for the background noise is derived (white, red or blue noise depending on the autoregressive (AR) coefficient of the signal[8]). Significance tests against the related noise are conducted within the signal spectrum and across the signals as well – this can be referred to as simultaneous testing. In case if the tests reject the presence of long memory effects, first differencing seems to be a more appropriate choice for detrending compared to fractional differencing, since the loss of long memory information is unlikely to occur. Therefore, the consideration of the long memory effect in Chapter 4 is different from the one in Chapter 3: Here, a specific log periodogram estimator as in Phillips (2007) is used to estimate $\hat{d}$. The Phillips (2007) regression based estimator can also be used as a unit root test, since it is consistent for d up to $d = 1$. If $\hat{d}$ is significantly different from one, applying first differences would most likely interfere with irregular and regular long-run fluctuations and create severe spectral distortions by over-amplifying higher frequencies. In addition, hypothetically, if $0 < \hat{d} < 0.5$, then one could also estimate the long memory effect by calculating the Hurst parameter. Yet, a brief graphical examination of the series on Figure 4.4 suggests that this is unlikely. The estimation of the differencing parameter and the test on the long memory effect allows us to check whether the data was over-differenced: in presence of such effects fractional differencing would be preferable; yet, depending on the reliability of the test applied, if the estimated difference parameter $\hat{d}$ is around one, first differencing can be used, as suggested by the estimation. However, one should bear in mind, that a unit root process may still contain elements of a process with long memory (see Ngai Hang Chan, 1995). Therefore, obtaining a benchmark signal may be associated with additional challenges.

The periodicites, which are not simultaneously significant against the background noise across the given types of signals (filtered and differenced), are likely to be spurious. The last chapter contains a deep analysis of the problem of spurious periodicities and a proposal to test for such cases. Whereas in the last chapter the real data are used, in the discussion the simulated data (see Fig. 5.1) is analyzed to show that filtering may indeed amplify lower frequencies, even if these were

[8] An AR coefficient of zero is related to a white noise model; whereas the AR coefficient <0 is related to the blue noise, with higher frequencies prevailing and >0 – to the red noise with lower frequencies prevailing.

not programmed during the simulations: the advantage of the simulated data in this methodological analysis is that the intrinsic periodicities are known by the design of the simulation. Bearing in mind the analysis in Chapter 4, the rule of thumb smoothing parameters and bands for statistical filters should be used with extreme caution, thus to prevent such rules of thumb from becoming a *self-fulfilling* prophecy.

1.2 Summary of the introduction

A brief summary of the introduction is necessary to ensure the transition for the articles, incorporated in the main body of the dissertation. Chapter 2 represents empirical analysis of the Malthusian cycles, mainly motivated by Crafts and Mills (2009), and considers the transition from the Malthusian regime to the post-Malthusian one. The interlinks between the population cycles and the economic cycles deteriorated due to a number of reasons, including the Smithian growth and institutional arrangements. This particular role of institutions, shaping economic constraints is discussed in this chapter in detail. In particular, the land laws and the seigneurial tenure regime can be seen as an example of such a constraint. An interesting target for empirical analysis of the Malthusian cycles and the transition from them is Canada, as a frontier economy: in a frontier economy land is abundant, yet cultivated land may be scarce. In Chapter 2 we empirically show that the Malthusian cycles, present in the frontier economy of Canada, have been dissolved due to gradual changes, for example market integration, as well as due to institutional changes, the conquest of Quebec and legal reforms. The transition from the Malthusian regime to the post-Malthusian one is accounted for by the means of structural break tests and sub-sampling. It is interesting to note that the structural break, dividing our sample into two sub-samples is seven years after the British conquest of Quebec in 1760, therefore, the empirical strategy accounts for institutional change as well. The analysis of gradual change is performed by rolling estimations of standard deviations of the data. In the given chapter we apply the short run analysis framework using VARs and cross validate our results obtained with the filtered fluctuations, by conducting the same analysis for the differenced data. The Malthusian cycles represented interrelated population and economic cycles. After the demographic change and the transition to the post-Malthusian regime, this relation broke down. In the subsequent chapters more emphasis is put on the economic cycles.

Fabian (1989) and Besomi (2011) provided main motivation and research background for Chapter 3, whereas Johansen (2008); Johansen and Nielsen (2012); Jones et al. (2014) provided motivation for the choice of methods: we conduct short run VAR and long-run FCVAR analysis for the interaction between bibliometric and economic variables. The previously mentioned statement "panics produce texts" is approached empirically with the aid of Granger-causality and long-run exogeneity tests. The FCVAR model allows us to include long memory effects and analyse fractionally cointegrated variables. The results show that large shocks and in particular downswings of business cycles serve as an impulse for fluctuations in bibliometric variables. The VAR analysis with the Kalman filtered cycles is validated by FCVAR analysis with fractional differencing. A discussion is made in order to elaborate on the predictive causality between the bibliometric and the economic variables. This inference provided insights in the far reaching implications of business cycle downswings as an exogenous stimulus in the research production function: crises fuel economic thought and new theories, models and methods emerge. In Chapter 3 we also discuss other potential direction of causality, e.g., from scientific output to the economy. The latter is open for further debates and could become the direction for further research.

Chapter 4 is motivated by numerous works, including Cendejas et al. (2015); Diebolt (2014); Metz (2011) on the frequency domain analysis and Pollock (2013, 2014); Woitek (1997) on the problem of spurious periodicities. In this chapter the well-established methodology of obtaining stationary cyclical fluctuations of economic variables is critically asserted: it is shown that specific detrending methods may cause the emergence of spurious periodicities. The vulnerability of filtering tools and their exposure to diverse distortions including the Slutzky–Yule effect is analysed in detail. Identification of spurious periodicites is conducted across different types of signals (filtered and differenced) in order to simultaneously test the spectral peaks against the related background noise. The findings warn researchers against blind usage of the rule of thumb smoothing parameters of the filters.

In the discussion, following the chapters with the articles, the contributions are summarized and an insight into further research, based on the current findings, is provided.

2

Malthusian pressures: empirical evidence from a frontier economy

by Vincent Geloso and Vadim Kufenko

Abstract

Summary. In this paper, we study Malthusian pressures in a frontier economy. Using the empirical data on real prices and demographic variables from 1688 to 1860 for Quebec and Montreal, we test for the existence of Malthusian pressures. Bearing in mind the particularities of frontier economies and the development of the Canadian economy, we conduct a Granger-causality analysis for the time-series of real wheat prices, birth and death rates with the help of VARs in order to identify positive and preventive checks. Using the Bai–Perron test we find a structural break in 1767 and divide the sample into pre- and post-conquest periods. We find that the positive checks were operating in the years prior to the conquest but that they faded during the nineteenth century. It follows that an increase in the wheat prices Granger-causes an increase in death rates in the pre-conquest period. Additional tests and a robustness check of the detrending methods are performed.

Keywords: Malthusian economy · Preventive check · Positive check · Canadian history · Empirical analysis

JEL classification: J11 · N11 · E32

2.1 Introduction

For most of human history, wages are fluctuated at the edge of the subsistence level, sometimes slightly above and sometimes slightly below it. Although technological innovations were not absent, most movements in living standards were determined by changes in population sizes. This reality has been labelled "Malthusian" in honour of Thomas Malthus. The key features of this model are that the supply of land is fixed and that this supply is small relative to the population. This applied very well to countries in Europe where these conditions were met, but what about New World economies from the seventeenth to nineteenth centuries which had only recently been settled?

Quebec, the modern day french-speaking province of Canada, is a good candidate to answer that question. Known as New France from 1608 to 1760 before it was taken from the French crown by the British and then known interchangeably as Quebec, Lower Canada and Canada East up to 1867, historians of this society have often portrayed it as a society rife with Malthusian pressures. The eminent Fernand Ouellet (1966) asserted that the colony lived through an "economic crisis" from 1802 to 1850 mainly because of soil erosion and overpopulation of the colony. According to Ouellet, grain price fluctuations were symptomatic of the underlying performance of the agricultural economy whose surplus fed into the other sectors of the economy.

This view is still commonly portrayed by popular historians (Bédard, 2012). This a surprising argument given that numerous authors have found that the land supply was still very large at the time specified by Ouellet (see Altman, 1983; McInnis, 1982). Moreover, the data from mortality rates and crude birth rates do not fit the Malthusian framework. The steepest increase in the mortality rate (indicative of the positive check) are found in the period of French rule when the land supply since less than 10% of the attributed estates of the colony were cleared for agricultural production in 1739. In the 1831 census, this proportion stood at 34%. But even by the mid-nineteenth century, that claim is dubious since the 1851 census reveals that only 44% of the total lands owned were improved.

The literature on Malthusian pressures in Canada and the United States is constrained by the absence of continuous data series. We try to fill in the gap. Thanks to the existence of numerous economics papers that detail operational procedures to test the existence of Malthusian pressures in economic history, filling this gap is made easier. It is possible that this lack of testing for Lower Canada and Quebec was the result of limited statistics with regard to economic indicators. Recent work by one of the current authors Geloso (2014a,b) has generated large databases of prices in the colony from 1688 to 1858. Combined with the exhaustive data already available with regards to vital statistics (crude mortality rate, crude birth rate, nuptiality rate), it is possible to run statistical tests. We find that

Malthusian pressures in the Quebec economy post-conquest were non-existent – at a time when the land supply was growing scarcer. In fact, we find evidence of Malthusian pressures in the pre-conquest period – at a time when land was more easily available.

2.2 The Malthusian Economy

Under Malthusian theory, real wages are not determined by the marginal product of labor but rather by the population sizes relative to the pool of available resources in a technologically stagnant environment (see Wrigley and Schofiled, 1981). Under the constraint of slow technological improvements, the first equation of the Malthusian model sets wages as a function of population. However, in the short run, population is endogenous to real wages. Births (the rate of population increase) are respondent to wages. Deaths also respond to wages. When real wages increase (decrease), births increase (decrease) while deaths decrease (increase). In the long run, the equilibrium rate of population is equal to zero. In the short run, an increase in real wages (reflected by a one-time technological shock) that increases productivity brings demographic behaviour out of equilibrium and population increases. However, the marginal product of labour will decline as more individuals compete for a fixed stock of capital, leading to lower real wages (mostly through higher prices). Two forces will act to restore equilibrium: preventive check and positive check. The preventive check refers to households delaying family formation. This may be expressed through later marriage ages, planned sexual activities, contraception, longer stays in the parental household and greater spacing between births. The positive refers to the impact of mortality increasing to force the population back to equilibrium level (Guinnane and Ogilvie, 2008).

It is these two checks that have been the topic of discussion amongst economic historians. More precisely, the discussion has centered on when the two checks disappeared. In England, Nicolini (2007) and Craft and Mills (2009) have argued that the two checks disappeared somewhere between the 16th and 18th century with the positive check disappearing earlier than the preventive check. However, in eighteenth century Germany, Fertig and Pfister (2012) found that the positive check was stronger and weakened slightly past 1815 and that the preventive check was equally strong throughout the period. According to these two authors, the weakening of the positive check was caused by greater market integration. Most of the research has concentrated on economies that were already densely populated.

2.3 Malthusian framework in the New World and Quebec

This theoretical framework works differently if there are large quantities of unused inputs. The concept behind Malthusian equilibrium is that inputs are being used more intensively for diminishing marginal returns. However, if there are unused resources to be introduced cheaply into production, an increase in population will not have these effects. In fact, in the short run, the larger population would increase prospects for specialization and would increase output very rapidly relative to inputs. One example of this is provided by Alvarez-Nogal and Prados De La Escosura (2013) in the case of Spain after the Black Death. Since Spain was at that time a frontier economy with more abundant land, the Black Death did not reduce pressures on scarce land resources; it merely eradicated commercial networks, isolated scarce populations and led to a decline in specialization.

This Spanish case shares similarities with North America prior to the first half of the nineteenth century. These were economies where land was a cheap input that could easily be introduced into production and an increase in population would not lead to falling real wages. Quebec qualifies as such an economy in our opinion. Yet numerous are the authors who would disagree (Greer, 1985; Ouellet, 1972, 1980; Russell, 2012). These authors have tended to explain the poor economic performance of Quebec up to the 1850s in great part upon Malthusian pressure. Ouellet has made this claim in a different manner pointing out that overpopulation was caused by a "shortage of fertile, easily accessible land" (see Ouellet, 1980, p. 144). Ouellet argued that this shortage was localized in some long-settled areas and individuals resettled in other parishes and townships in the colony (ibid, p. 156). These new parishes would have been on marginally less productive lands. Along these lines, and although he never uses the term, Ouellet is arguing for the existence of a preventive check. According to this framework, the pressures materialized thanks to inputs that were costly to introduce into production and whose productivity was marginally lower than previously settled lands. Haines (2000, pp. 168–169) defended his claim that there existed evidence of a preventive check in New England in the form of high costs of household formation. More broadly, the claim of economic distress in Quebec is attributed to the rapid increase in the rural population whose effects were amplified by exogenous shocks like the Hessian fly and the wheat midge as well as a supposed innate conservatism amongst the French-Canadians that made them less efficient than English-Canadian households Le Goff (1974). However, this approach by Ouellet is at odds with another of his claims. Arguing that French-Canadian farmers were conservative towards new farming practices, Ouellet then added that this cultural conservatism expanded to fertility patterns. If these patterns were culturally determined, the preventive check would have been weaker because of their cultural component and the positive check stronger. Moreover, claims of culturally determined fertility patterns are often exaggerated (also hard to prove) as shown by Zhongwei (2006, p. 10, 13 and 27) for the case of China where similar claims have been made.

Paquet and Wallot (2007) countered this line of argument by denying that the economy was performing poorly. In doing so, they negated the existence of any significant pressures along the lines proposed by Malthus. They pointed out that the economy of Lower Canada was diversifying into products like timber, potash and pearl ash. Bédard and Geloso (2014) have advanced evidence supporting this view that economic growth was positive in the first half of the nineteenth century. McInnis (1982) also feeds this line of argument by pointing out that colonists in Quebec exported timber to England and imported wheat from Upper Canada, which places the performance of the agricultural economy (whose decline is central to the claim of Malthusian pressure) in a more positive light. Courville and Séguin (1995) and Courville (1990, 2008) also noted a distinct trend in favour of diversification in the form of new villages and small towns appearing in the countryside. Increased urbanization is contradictory to the Malthusian model as Becker and Murphy (1999) pointed out. Greater population density promotes specialization and greater investment in human capital. These "increasing returns from specialization would raise per capita incomes as population grew and are likely to be far more important than diminishing returns in resource-constrained sectors" (see Becker and Murphy, 1999, p. 146). However, this is a question of degree. It is possible, under the Malthusian model, for both population and economic growth to be positive if there are improvements in productivity and technological settings. Hence, observing positive growth, as Paquet and Wallot do, does not invalidate the existence of Malthusian pressures. Haines (2000) makes the claim that the United States did manage to generate fast economic growth on a per capita basis in the antebellum era while there was a preventive check operating. All of the facts highlighted above suggest that the literature is at an impasse, which can only be settled through empirical testing.

2.4 Data

Wheat prices were selected because of their importance in the diets of the French Canadians. According to Fyson (1992, p. 74), 56% of the diets of workers in Lower Canada came from starches. But this is a conservative estimate since Vallieres and Desloges (2008) put this proportion above 60% in urban areas during the New France era and close to 70% in rural areas during the same era. Given this great importance of wheat, it should be seen as a good measure of the variation in the standard of living. "From one year to the next, fluctuations in the price of grain were the primary determinants of variations in the real wage" (Galloway, 1988, p. 276), since nominal wages were relatively stable from year to year (see

Geloso, 2014b, for New France). The prices collected for wheat stem in part from Geloso (2014a) for the pre-conquest era and from Ouellet et al. (1982) for the post-conquest era. Both these price series should be seen as wholesale prices collected from the account books of religious congregations. Market exchanges were thus always an open option the habitant farmer. Even if he chose not to trade his labor on the market, he could always do so at the prevailing price. Most peasants in Quebec produced for themselves, but they always tried to sell part of their crop to the fifth of the population in urban areas in exchange for money that would allow them to acquire imported goods like cloth, sugar, pepper and salt. For the Montreal area prior to the conquest, we have used the price series produced by Dechene (1994) which is also illustrative of wholesale prices. Prices were deflated over the broad price index produced by Geloso (2014a) which was combination of his own price index for the pre-conquest era with that of Paquet and Wallot (2007).

The vital statistics we have used have been drawn from multiple sources. The raw numbers of births and deaths have been drawn from the work of Langlois (1935) and concern only the Catholic population. In order to provide births and deaths relative to population, we have relied on the Catholic population estimates from Henripin and Péron (2000). We do not believe that the focus on the Catholic population is problematic. The Catholic population of Quebec was predominantly French while the non-Catholic population tended to be English-speaking. By 1861, the vast majority of the population (85%) was Catholic making our concentration on Catholic warranted (see Pelletier et al., 1997, p. 93). According to the 1851 census of Canada East (as Quebec was then known), the mortality rate observed in predominantly English-settled areas were equal to those of French-settled areas (see Public Archives of Canada, 1873). Some differences emerge in closer studies. For example, studies concerned with late nineteenth century show that Catholics had a higher rate of infant mortality (see Gauvreau and Gossage, 2001). Catholics also tended to marry earlier than Protestants in the city of Montreal in the 1860s and their mortality rate was higher (see Olson and Thornton, 2011, pp. 154 and 62). Differences were also observed in the average family size. Yet, this fact could be used to support our conclusions. As we will see later, we find the absence of the preventive check and positive check after 1760. If the Protestants were doing better than the poorer Catholics who exhibited greater birth rates and mortality rates while the two Malthusian checks operating upon the Catholics were disappearing, this means that the case we are making in this paper is quite conservative. Any attempt at including time series from the Protestant minority would reinforce the strength of our results. Moreover, the focus on Catholics is justified in order to solve the impasse discussed above. Those who hold the position that there were population pressures have largely focused on the Catholic population, which was believed to be poorer than the Protestant population. Since poorer populations tend to be more susceptible to Malthusian pressures (through poorer nutrition, poor diets and a lesser ability to withstand shocks), the focus on the Catholic population is warranted. If they did not experience Malthusian pressures, it is quite unlikely that Protestants experienced them as well.

Normally, we would opt for the inclusion of a variable for infant mortality. If there were a positive check with regard to the population through higher mortality, it would have been felt more strongly for younger individuals whose immune systems were not fully developed—namely children. The problem is that the dataset we use does not differentiate mortality on the basis of age; it is merely the crude mortality rate. However, there is a mortality quotient provided by Gentil (2009). Gentil estimates infant mortality in Quebec up to 1779 and even has regional breakdowns (Quebec city, Montreal, Trois-Rivières and rural areas). While it is tempting to use the above-mentioned estimates to refine ours, Gentil's data is not suited to any such attempts. Her mortality quotients do not cover the full population and concentrate on the mortality of legitimate children whose mortality rate was considerably below that of illegitimate children. Hence, using these data could lead to some bias. However, papers like those of Nicolini (2007) and Craft and Mills (2009) have relied on the broader crude mortality and crude birth rates with sufficiently robust results.

Wars and climate in this economy would have been very problematic and could potentially disrupt any statistical analysis if no control is attempted. Consequently, we have included a war dummy variable throughout the sample, which we combined with the climate dataset provided by Mann et al. (1998). The war dummy is straightforward and includes also the rebellions of 1837–1838 in Lower Canada as well as the international wars the colony was brought into from 1688 to 1860. The climate variable is expressed in deviation from the average temperature observed between 1961 and 1990. Although other climate datasets exist (McIntyre and McKitrick, 2003), we have opted for the more often cited dataset by Mann et al. (1998). Other factors (technology, public health, urbanization) that could influence our tests were negligible. There was very little technological innovation during our period of study. The predominant sector of agriculture would not benefit from new technologies like the mechanical reapers until the 1850s (which is the last decade of our study). Other innovations like refrigeration (which would eventually allow the boom in dairy production in Quebec) would also arrive later in the century. Railways could have contributed, but by the 1830s, few miles had been constructed and a truly inter-colonial network of railways only emerged after Confederation in 1867. With regard to advances in health care, most of the public health infrastructure began to emerge in the 1840s onwards (see Vallieres and Charbonneau, 2008, p. 833). There had been some health institutions prior to the 1840s like that established by the Augustine congregation of Quebec City, but they had always been confined to urban areas and were modest in terms of mission relative to the public health efforts deployed in the years preceding Confederation. The importance of public health improvements would tend to appear mostly after our period of interest. At this point, we can also rule out urbanization. Up to the 1851 census, the share of the population living in the three large urban centers of Quebec (Quebec City, Trois-Rivières and Montreal) declined progressively. Table 2.1 shows that individuals were leaving towards the countryside from 1688 to 1851. However, this trend should be divided in two. Prior to the 1780s, individuals were leaving for the countryside and no new urban centres appeared. After that point, urbanization was driven mostly by the formation of villages and small towns in the countryside, not by the growth of large cities (Courville, 1990). Hence, the share of all inhabitants living in all cities, towns and villages increased from the 1810s onwards. In those villages and small towns, mortality rates were very much in line with those generally experienced in the countryside. Had we expanded our period of interest beyond the 1850s, this would have been a problem. However, it does not represent a problem before that point in time. Moreover, when we compare our data with that of Vallieres and Charbonneau (2008, p. 870), we find that they share similar trends (Fig. 2.1).

Table 2.1: Share of the population living in the three urban centres, 1688 to 1891

Year	Share
1688	25.80%
1739	23.30%
1765	22.00%
1825	11.80%
1851	11.70%

Source: Public Archives of Canada (1873) and Government of the Province of Canada (1853)

2.5 Empirical strategy, methods and results

We begin with testing the key variables, real wheat prices, birth and death rates on stationarity. We apply the Augumented Dickey-Fuller test with Generalized Least Squares (further ADF GLS) estimation as in Elliott et al. (1996) which performs better in small samples comparing to the original version of the test using the Order of the Least Squares (OLS) estimation. The optimal lag length of the test is selected according to the Akaike Information Criteria (further AIC) as in Akaike

(1974)[1]. Thus, we report the test statistics at the optimal lag[2] in Table 2.2. As it follows from the test, all of the levels of the three key variables are not stationary and need to be transformed. This test result implies, that prices and population in Canada during 1688-1860 were unstable. The subsequent step is to choose an appropriate specification: a vector error correction model (VECM) or a vector autoregression (VAR). To do so, we require a cointegration test, since if the series are cointegrated we need to include a cointegrating vector in the specification; otherwise, a VAR framework would be appropriate.

Fig. 2.1: Original data

One has to note that the cointegration test is merely a tool in selecting an appropriate specification for causal inference of the relation between real wheat prices, birth and death rates. We have given preference to the Johansen cointegration (Hamilton, 1994; Johansen, 1988, see Ch. 14) test due to its multivariate framework and a good performance on finite samples, as stated in Dhrymes and

[1] In order to preserve methodological consistency we will apply the AIC lag selection method for further estimations in the paper. We double check the lag length with the Wald lag-exclusion test.

[2] In the ADF GLS test for wheat prices the AIC determined optimal lag is 8; for birth rates it is 2 and for death rates the optimal lag length is 10.

Table 2.2: Augmented Dickey-Fuller test, GLS version

Variables	Test statistic	Critical value (5%)
Wheat price	-2.258	-2.874
Birth rate	-1.271	-2.943
Death rate	-2.121	-2.846

Dimitrios (1997). The optimal number of lags[3] is determined by the AIC, as in the ADF GLS test. As we observe from Table 3.8, the trace statistic exceeds the critical value dramatically and therefore we reject the null hypothesis of a presence of a cointegrating vector[4] in a system of prices, birth and death rates. The implication of these results is the rejection of the VECM in favor of the VAR specification.

Table 2.3: Johansen Cointegration test

Rank	Trace statistics (2nd Rank)	Critical value (5%)
0	107.5706	29.68
1	46.8626	15.41
2	12.5723	3.76

Further we investigate the interaction between the cyclical fluctuations. The time frames of our analysis are 1688–1860. As we have noted before, during this period a number of historical events took place and the economy of Canada and its structure have changed dramatically. Therefore, we would like to test our data on structural breaks for which we apply the package from Zeileis et al. (2002). The first step is to determine the potential number of the structural breaks with the help of the Bayesian Information Criterion (BIC) resembling the tests applied in Hall et al. (2013). As it follows from Figure 2.2, the minimum values of the BIC point out a single break. Therefore we proceed with an F test as in Bai and Perron (2003) to identify the time point. The results of the structural break test considering wheat prices[5] are depicted on Figure 2.3. The F statistics suggests that the break-point occurred in 1767, which is roughly seven years after the British

[3] In the Johansen cointegration the AIC determined optimal lag length is 2.

[4] The Malthusian pressures are usually analyzed in the short-run (see Nicolini, 2007); however, the methodology requires us to avoid specification errors and thus in a presence of a cointegrating vector we would have to include one in our model. Since we do not find cointegration, we apply the VAR framework, which appears to be the appropriate specification in this case.

[5] The Bai–Perron test applied to birth and death rates yields different results: at the end and beginning of our time frames, which would not allow us to divide the time-series into subsamples.

conquest[6]. This allows us to divide the sample into two periods for the analysis according to historical events: we treat the data according to two periods, the pre-conquest or 1688–1767 and the post-conquest or 1768–1860.

Fig. 2.2: BIC test on the number of structural breaks

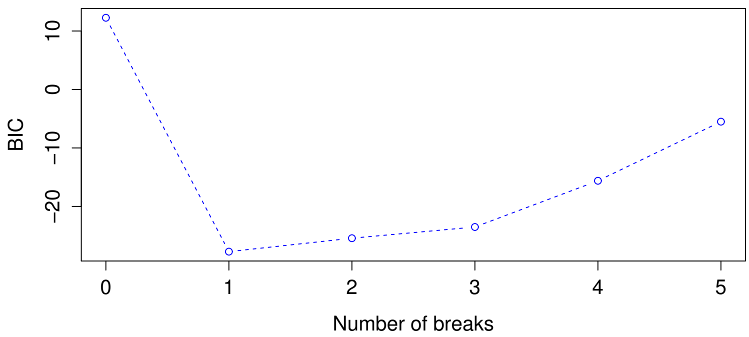
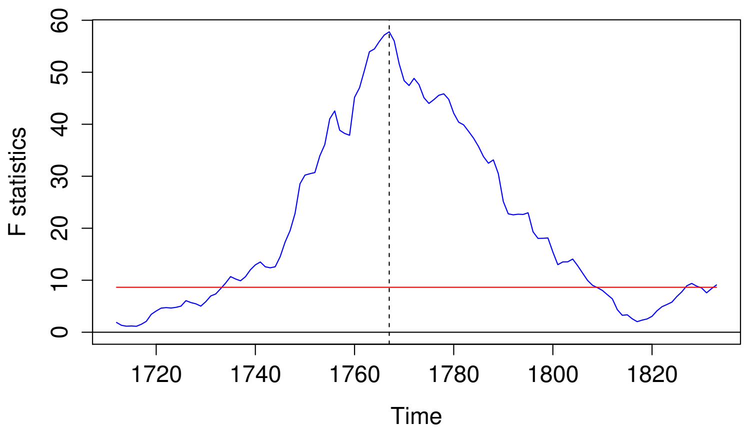


Fig. 2.3: Bai–Perron structural break test



[6] Given the risk of spurious structural breaks, mentioned in Hall et al. (2013, p. 61), we validate the result obtained with the F test by applying the Cumulative Sum test (CUSUM) as in Ploberger and Kramer (1992). The latter test is capable of detecting multiple breaks, however in our case the only extreme point is located at 1767, which validates the result of the F test.

First of all, let us examine the descriptive statistics of our key variables: real wheat prices, birth and death rates. According to the results from Table 2.2, we required a transformation to achieve stationarity. In order to perform detrending and obtain cyclical fluctuations ($y_t - \tau_t$) we apply filtering with the Hodrick–Prescott filter (further HP) to remove the trend and achieve stationarity. Below is the minimization problem of the HP filter. For demonstration we choose 6.25 for λ as in Ravn and Uhlig (2002, p. 374). The HP filter (see Hodrick and Prescott, 1997, p. 3) penalizes the series up to the second order and all of our series are I(1), which should not cause any distortions.

$$\min_{\tau} = \left(\sum_{t=1}^{T} (y_t - \tau_t)^2 + \lambda \sum_{t=1}^{T} [(\tau_t - \tau_{t-1}) - (\tau_{t-1} - \tau_{t-2})]^2 \right) \tag{2.1}$$

We obtain detrended data that represent cyclical fluctuations in prices and in birth and death rates. Further we use the detrended cyclical data for the descriptive statistics and for the time series Granger-causality analysis. Let us first examine the descriptive statistics of the filtered cycles.

Table 2.4: Descriptive statistics for I (1688–1767) and II (1768–1860)

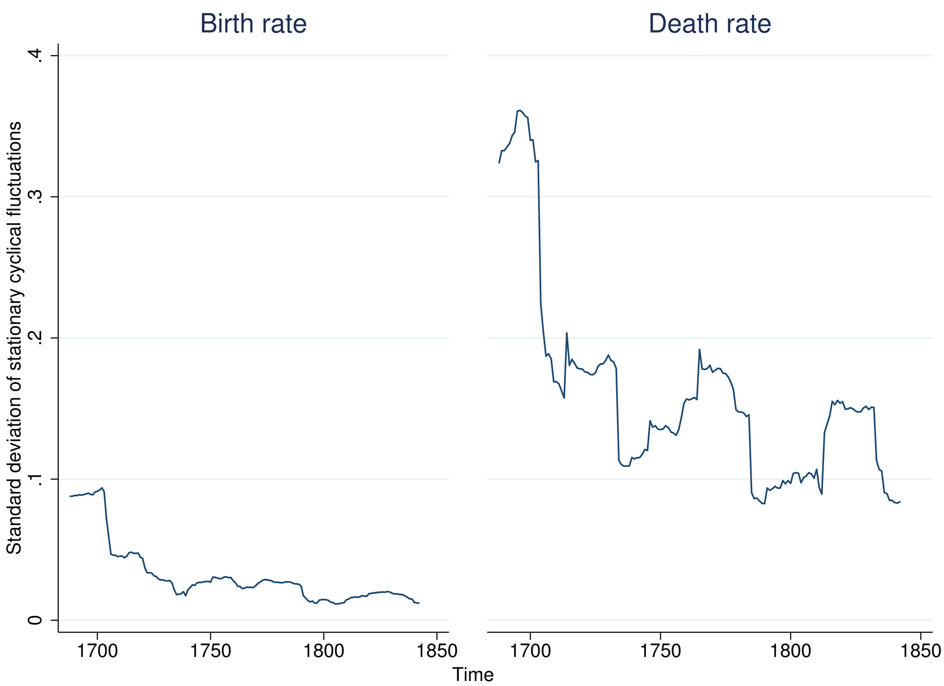
Variable	Obs.		Std. Dev.	
	I	II	I	II
Wheat prices (cycles)	80	91	0.15688	0.12515
Birth rate (cycles)	80	93	0.0524	0.01963
Death rate (cycles)	80	93	0.2147	0.12566

Let us consider descriptive statistics from Table 2.4 for the main variables of interest. It appears that in the second period prices, birth and death rates have become less volatile: the standard deviation of prices decreased by 20.3%, of birth rates by 62.5% and of death rates by 41.5%. We observe narrower cyclical price fluctuations which implies a decrease in volatility of all variables. Indeed, the period after 1767 appears to be less volatile in terms of demographics; however, one has to question whether this was a smooth change or a discontinuous change. Fig. 2.4 depicts rolling standard deviation of birth and death rates. From Fig. 2.3 we can tell that there was a structural break in wheat prices after 1767; however, the demographic variables did not display such obvious structural breaks and therefore we depict rolling standard deviations[7] of the related series on Fig. 2.4. There

[7] In order to obtain smooth results we use a window of 20 observations and set the smallest step of 1.

are two important points to highlight: firstly, the standard deviation of birth and death rates gradually decrease after 1740–1760, exhibiting occasional humps. Secondly, the decrease in demographic volatility was gradual; however, we should note that most of this decrease took place in period II (1768–1860). The latter fact is confirmed by the descriptive statistics from Table 2.4.

Fig. 2.4: Rolling standard deviation of cyclical fluctuations



Descriptive methods allowed us to capture changes in the fundamental time-series characteristics: decreasing volatility. This decrease of volatility in real wheat prices and in birth and death rates in the post-conquest period of our analysis requires a thorough investigation of the causal interaction between these variables. In order to perform such an analysis, we have selected the well established VAR framework, as in Hamilton (1994, Chpt. 11) and the Granger-causality test, as in Granger (1969). The cyclical fluctuations, obtained with the help of the HP filter, are stationary and can be used for the VAR analysis and Granger-causality testing with the help of the following model[8]:

$$\begin{pmatrix} y_{1,t} \\ y_{2,t} \\ y_{3,t} \end{pmatrix} = \begin{pmatrix} c_1 \\ c_2 \\ c_3 \end{pmatrix} + \begin{pmatrix} \pi^1_{11}\pi^1_{12}\pi^1_{13} \\ \pi^1_{21}\pi^1_{22}\pi^1_{23} \\ \pi^1_{31}\pi^1_{32}\pi^1_{33} \end{pmatrix} \text{x} \begin{pmatrix} y_{1,t-1} \\ y_{2,t-1} \\ y_{3,t-1} \end{pmatrix} + \begin{pmatrix} e_{1,t-1} \\ e_{2,t-1} \\ e_{3,t-1} \end{pmatrix} \tag{2.2}$$

Where $y_{1,t-1}$ denotes cyclical fluctuations in the real wheat prices; $y_{2,t-1}$ denotes cyclical fluctuations in birth rates; $y_{3,t-1}$ denotes cyclical fluctuations in death rates; C denotes a constant, whereas π denotes coefficients; e is an error. In addition, we include exogenous controls into the model: dummies for war periods and temperature change. Let us investigate the results in Table 2.5 the pre-conquest period (1688—1767). Using temperature change and war dummies for periods of war clashes as exogenous controls, we have obtained the following result: the first lag of the change of the real wheat prices has a positive impact on the death rates with 0.286%. This effect of a positive check is significant on 5% level. Naturally, this is confirmed by the Granger-causality test in Table 2.7 for specifications 1, 2 and 3. From the test in follows, that cyclical fluctuations of the real wheat prices Granger-cause cyclical fluctuations in death rates. For period I this effect is valid on the 5% level. The second effect is related to lagged birth rates Granger-causing death rates. This effect is also positive and significant on 5% level. We associate this effect with infant mortality and note that in the post-conquest period it vanishes. The preventive check was not discovered. One should note that in period I the climate control was significant in the equation for the real wheat prices, whereas in the post-conquest period it was significant in the equation for the birth rates.

Post-conquest period results from Table 2.6 seem to be different: the lags of the cyclical fluctuations of the wheat prices is insignificant for the death rates. The causal effect vanishes which is confirmed by the Granger-causality test in Table 2.8. The results suggest no preventive or positive check in this period. However, we note significant impact of wars and temperature change, as exogenous controls, on the birth rates (see Table 2.6). Therefore, we can conclude that the causal effect of real wheat prices on demographic variables vanishes in post-conquest period, after 1767. This is consistent with the decreases in demographic volatility after 1740–1760, depicted on Fig. 2.4.

[8] For the simplicity a one-lag model is described. The number of lags to be included is determined by the AIC and the Wald lag-exclusion test. We have tested specifications up to the 10th lag and the Wald lag-exclusion test showed no substantial benefits from including lags further than 6. The latter specification with 6 lags outperformed specifications with fewer lags according to the Likelihood Ratio test and the AIC. Therefore, the optimal specification used for our estimations includes 6 lags.

Table 2.5: Pre-conquest period, HP filter, 1688–1767

Variables	(1) Wheat price	(2) Birth rate	(3) Death rate
Wheat price, lag 1	-0.384***	0.00686	0.286**
	(0.102)	(0.0375)	(0.120)
Wheat price, lag 2	-0.599***	-0.0279	-0.229*
	(0.104)	(0.0383)	(0.123)
Wheat price, lag 3	-0.769***	1.58e-06	0.225*
	(0.114)	(0.0418)	(0.134)
Wheat price, lag 4	-0.549***	-0.00441	0.0606
	(0.107)	(0.0394)	(0.127)
Wheat price, lag 5	-0.417***	0.0101	-0.192
	(0.104)	(0.0381)	(0.122)
Wheat price, lag 6	-0.462***	-0.00777	0.186
	(0.107)	(0.0392)	(0.126)
Birth rate, lag 1	0.149	-0.752***	1.777***
	(0.353)	(0.130)	(0.416)
Birth rate, lag 2	0.312	-0.422***	0.586
	(0.426)	(0.157)	(0.503)
Birth rate, lag 3	0.0547	-0.533***	1.656***
	(0.415)	(0.153)	(0.489)
Birth rate, lag 4	-0.152	-0.600***	1.750***
	(0.419)	(0.154)	(0.494)
Birth rate, lag 5	-0.0406	-0.453**	1.064*
	(0.461)	(0.170)	(0.544)
Birth rate, lag 6	-0.286	-0.192	-0.0197
	(0.370)	(0.136)	(0.437)
Death rate, lag 1	0.0164	0.0376	-0.131
	(0.0988)	(0.0363)	(0.117)
Death rate, lag 2	0.208**	0.0116	-1.029***
	(0.101)	(0.0370)	(0.119)
Death rate, lag 3	0.0621	-0.0114	-0.0952
	(0.115)	(0.0421)	(0.135)
Death rate, lag 4	0.115	-0.0612	-0.543***
	(0.119)	(0.0437)	(0.140)
Death rate, lag 5	0.0688	-0.00982	0.00159
	(0.0913)	(0.0336)	(0.108)
Death rate, lag 6	-0.00574	-0.0209	-0.273**
	(0.0888)	(0.0326)	(0.105)
diff_temp_mann	2.861**	-0.0257	-2.423
	(1.304)	(0.479)	(1.538)
war	0.0427	-0.00378	-0.0345
	(0.0265)	(0.00976)	(0.0313)
Constant	-0.0318*	0.00134	0.0235
	(0.0175)	(0.00644)	(0.0207)
Observations	74	74	74

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2.6: Post-conquest period, HP filter, 1768–1860

Variables	(4) Wheat price	(5) Birth rate	(6) Death rate
Wheat price, lag 1	-0.129	-0.0450**	0.0593
	(0.116)	(0.0204)	(0.122)
Wheat price, lag 2	-0.732***	0.0267	-0.114
	(0.114)	(0.0201)	(0.120)
Wheat price, lag 3	-0.516***	-0.0259	0.129
	(0.132)	(0.0231)	(0.138)
Wheat price, lag 4	-0.469***	-0.00427	0.0970
	(0.133)	(0.0234)	(0.139)
Wheat price, lag 5	-0.182	0.000289	-0.0585
	(0.119)	(0.0208)	(0.124)
Wheat price, lag 6	-0.156	-0.00526	0.143
	(0.118)	(0.0206)	(0.123)
Birth rate, lag 1	0.857	-0.406***	0.879
	(0.603)	(0.106)	(0.630)
Birth rate, lag 2	-0.407	-0.339***	0.759
	(0.591)	(0.103)	(0.617)
Birth rate, lag 3	-0.573	-0.286***	0.597
	(0.603)	(0.106)	(0.629)
Birth rate, lag 4	-0.183	-0.223**	0.475
	(0.572)	(0.100)	(0.597)
Birth rate, lag 5	0.709	-0.270***	-0.0312
	(0.552)	(0.0967)	(0.576)
Birth rate, lag 6	-0.242	-0.139	1.757***
	(0.551)	(0.0965)	(0.575)
Death rate, lag 1	0.0374	0.0244	-0.538***
	(0.0941)	(0.0165)	(0.0983)
Death rate, lag 2	-0.121	0.00809	-0.586***
	(0.101)	(0.0177)	(0.106)
Death rate, lag 3	0.0276	0.0160	-0.714***
	(0.105)	(0.0184)	(0.110)
Death rate, lag 4	-0.0740	0.0196	-0.577***
	(0.105)	(0.0183)	(0.109)
Death rate, lag 5	0.0179	0.00552	-0.430***
	(0.0999)	(0.0175)	(0.104)
Death rate, lag 6	0.0877	-0.00683	-0.169*
	(0.0936)	(0.0164)	(0.0977)
diff_temp_mann	-0.708	0.636***	-0.893
	(0.997)	(0.175)	(1.041)
war	-0.0199	0.00723**	0.00221
	(0.0206)	(0.00361)	(0.0215)
Constant	0.00785	-0.00209	-0.00304
	(0.0124)	(0.00217)	(0.0130)
Observations	88	88	88

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2.7: Granger causality test for 1, 2 and 3

1688–1767		P > chi2	
Equation	Excluded	HP filter	Growth rates
Wheat price	Birth rate	0.871	0.9761
Wheat price	Death rate	0.43	0.9324
Birth rate	Wheat price	0.9811	0.3905
Birth rate	Death rate	0.1999	0.3766
Death rate	Wheat price	0.0107**	0.011**
Death rate	Birth rate	0***	0.0004***

*** p<0.01, ** p<0.05, * p<0.1

Table 2.8: Granger causality test for 4, 5 and 6

1768–1860		P > chi2	
Equation	Excluded	HP filter	Growth rates
Wheat price	Birth rate	0.2881	0.0837
Wheat price	Death rate	0.4233	0.4831
Birth rate	Wheat price	0.2358	0.3363
Birth rate	Death rate	0.6513	0.6408
Death rate	Wheat price	0.5717	0.3803
Death rate	Birth rate	0.1037	0.3245

*** p<0.01, ** p<0.05, * p<0.1

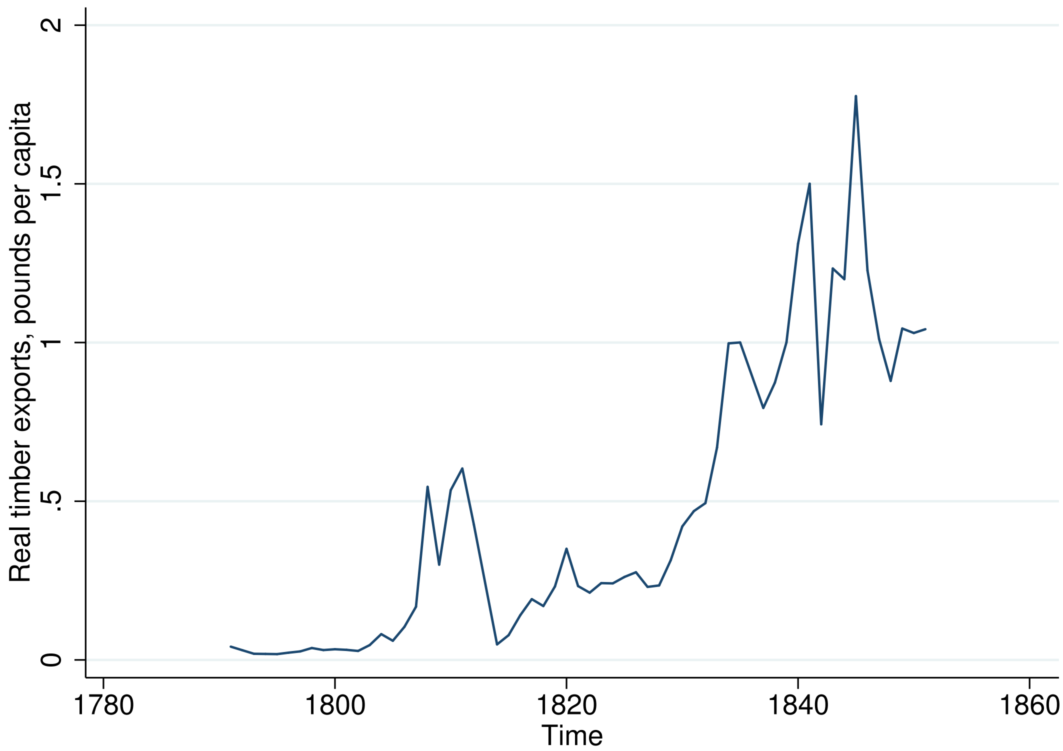
Additionally we perform a robustness check of our estimations using simple growth rates of the original series, as an alternative to detrending with the HP filter. This would ensure that the Granger-causality test results are not sensitive to the detrending methodology. The Granger-causalities with growth rates are presented in Tables 2.7 and 2.8 on the right. The test results confirm the ones obtained from the filtered series: in the pre-conquest period on the 5% level we observe Granger-causality from the growth rates of wheat prices to death rates and from the growth rates of birth rates to death rates as well. Similarly, in the post-conquest period none of the Granger-causalities are detected. Therefore, the presence of the positive check is robust to the detrending methodology. Finally, we verify that the residuals of our models pass the Portmanteau Q test for the white noise on the 5% level as in Ljung and Box (1978).

2.6 Discussion and conclusion

In this paper we focused on the causal inference of the relationship between real wheat prices, birth and death rates. We found that when it was under French rule, Quebec did seem to exhibit signs of population pressures in the form of the positive check. We found that fluctuations in wheat prices Granger-cause fluctuations in death rates in the pre-conquest period. However, after the conquest of Quebec by the British, the positive check disappeared. These are surprising results given that the literature that argues for population pressures locates them in the era of British rule.

We believe that our results can be explained through two possible channels: migration and market efficiency. Throughout our studied period, migration was mostly possible past the conquest. It is quite possible that French-Canadians mitigated demographic pressures through migration to the United States. Paquet and Smith (1983) provide evidence for such an argument, pointing out that there was a large migration flux of French-Canadians. Unfortunately, their data is not annualized and we only possess conjectural estimates that, on average, roughly 9000 French-Canadians left Lower Canada for other colonies between 1831 and 1851 (see Paquet and Smith, 1983, p. 440). However, their own analysis suggests that the bulk of the migration occurred in the 1830s – a decade of poor economic performance. Indeed, those years were marked by the wheat midge, epidemics and political rebellion. Yet, the 1840s exports and imports data (Vallieres and Desloges, 2008) suggest a recovery of economic activity which compensated for the unfortunate decade of the 1830s. Furthermore, the rate of population growth did not seem to have decelerated considerably between population estimates. While the compound rate of population growth was 1.8 % between 1831 and 1844, it bounced back to 3.56 % between 1844 and 1851 and to 2.76 % between 1851 and 1861. Moreover, there was also a steady positive flow of British settlers to Canada and Quebec, which also went through a lull in the 1830s before picking up in the 1840s and 1850s(see McInnis, 2000, p. 386). Anyhow, the reversal of population movements away from Canada is more relevant in the second half of the nineteenth century – a period beyond the focus of this paper (see McInnis, 2000, p. 416). As a result, we are not convinced that emigration – although a relevant factor – was sufficient to distort the impact of Malthusian pressures in the latter period.

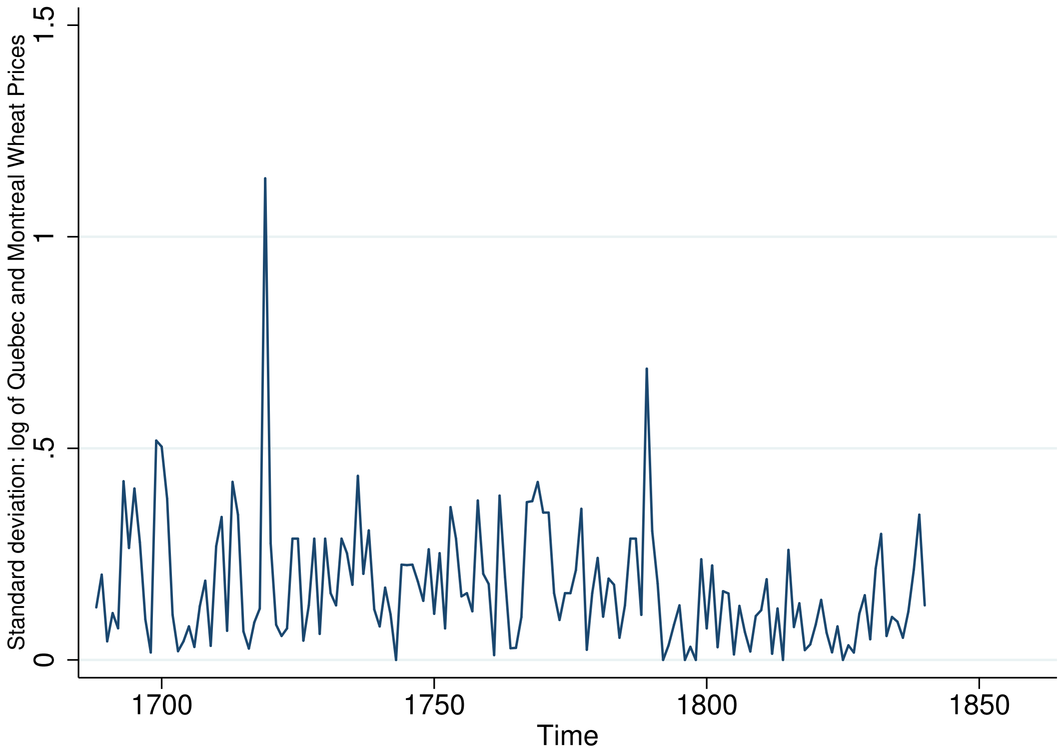
Fig. 2.5: Timber exports



The other explanation that we find more convincing is that of institutions which made markets more efficient. At this point, the logic presented by Boserup (2005) can be useful. Instead of population growth slowing down to equilibrium level associated with the given technologies, population growth leads to the adoption of new methods of production. Cultivators have a wide set of production possibilities via different mixtures of capital and labour inputs. They choose the mixture that reflects best the relative scarcities of these inputs. As population increases, they shift to new techniques that prevent output from falling. According to Boserup, this implies a decline in productivity. However, her model is concerned only with a one-sector economy (agriculture). If productivity increases in agriculture, households could decide to shift labour inputs to other non-agricultural sectors. Moreover, if productivity increased in other sectors, households could be tempted to sacrifice on leisure and use the freed labour inputs on other markets. These latter two forms of development would still appear to be close to the Malthusian ceiling of production and yet there would still be an increase in living standards if they occurred. Such developments are well illustrated in the work of De Vries (2008) regarding the “industrious revolution”. Reduction in transaction costs allowed the labor market to better coordinate employers and employees, leading to greater allocative efficiency and to greater incentives to intensification.

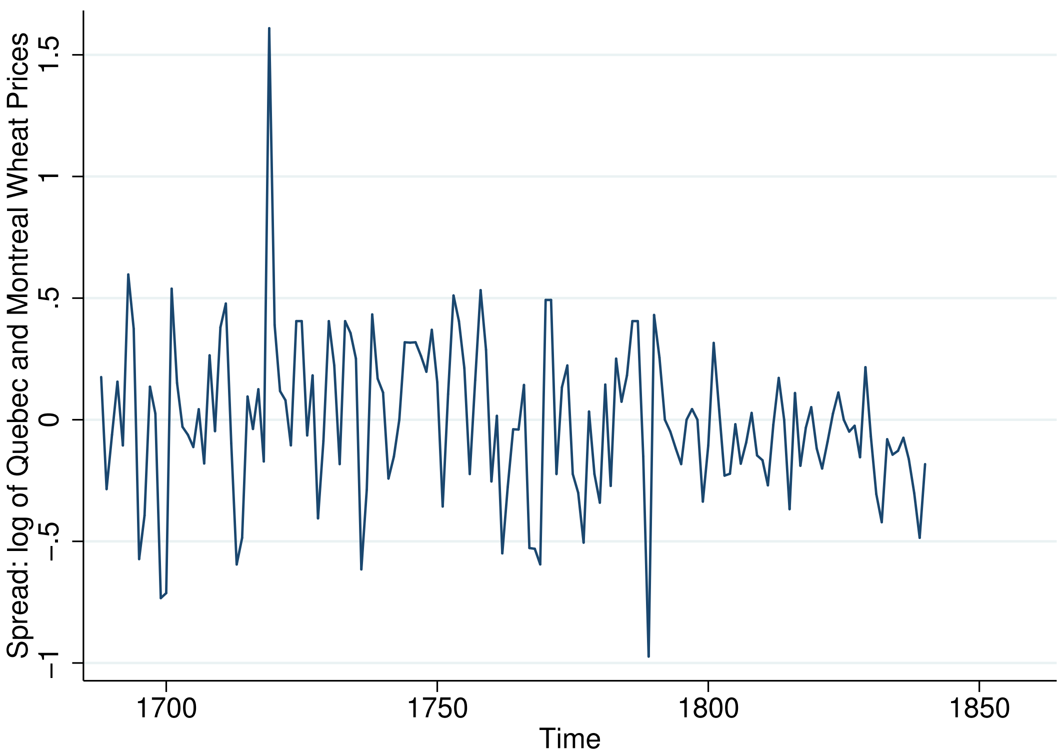
This logic of greater market efficiency explains the absence of the Malthusian checks after the conquest. First of all, the larger population of Quebec allowed for thicker markets to be formed which means more trade opportunities. As trade opportunities become more easily available, arbitrage opportunities also become exploitable. This implies that local supply shocks are eased thanks to the ability of merchants to ship grain around leading to some price equalization in the colony. In our case, the data supports the idea that markets grew increasingly integrated after the conquest and they began to move closely together after 1790 as can be seen with the diminishing price gap between the different cities of the colony (see Figs. 2.6, 2.7). This is a first channel by which increased population might not have led to the operation of either the preventive or the positive check. Second, households would have shifted inputs away from agriculture as they could now rely on providers outside their local markets (or even outside the household). In this case, they could work in other areas in order to acquire a monetized income and then complement this income with a small sized farm. Such a channel could have easily materialized through the emergence of the timber trade. Households in Quebec would have allocated inputs to the timber trade (or even the winter shipyards on the banks of the St-Lawrence river (Dufour, 1981), sold the timber on British markets and bought wheat from the neighbouring colony of Upper Canada. Up to the early nineteenth century, furs had been the main exports of Quebec, but this trade occupied only a small share of the population. However, once the timber trade progressively replaced the fur trade, it occupied a much larger share of the population. Households would have shifted inputs away from agriculture to harvest wood, which they could sell to merchants who would then resell it in England. Figure 2.5 illustrates the importance – on a per person basis – of the increase in the timber trade throughout the nineteenth century. This specialization would have allowed households to better tolerate higher wheat prices because incomes were substantially higher. This argument is strengthened by the fact that throughout the early nineteenth century, trade with the United States was also progressively liberalized. This is well exemplified by the 1831 Colonial Trade Act, which allowed American grains and flour to enter freely into Canada and allowed Canadians to sell timber to Britain and buy wheat from the Americans.

Fig. 2.6: Decrease in price deviations between Quebec and Montreal



This greater level of market efficiency is well supported by many forms of secondary evidence. First of all, as Bédard and Geloso (2014) underlined, the rise of banking in Quebec which was allowed by the local legislatures allowed the emergence of a network of private bank notes which eased denominational shortages of small currency. Secondly, the British domination over the seas allowed for safer trade and hence allowed the timber trade to expand in the colony to previously unseen levels. Thirdly, trade policy with the United States and other areas was progressively eased allowing for trade to become relatively freer than it had been under French rule. Combined with greater populations within the colony (allowing trade networks to form), this would have also played in favour of increased specialization and hence in favour of the diminution of the preventive and positive checks. Finally, the British also allowed land settlement past 1791 to be outside the realms of seigniorial tenure – whereby the person who farmed the land never owned it – and rather under the British law whereby one owned his farm plot. This would have allowed greater investments in agricultural techniques. Taken together, these factors would have mitigated Malthusian pressures. One important sign in our results that support this claim is the disappearance of the relation between birth rates and death rates during the post-conquest era. The disappearance of this link means that some form of demographic transition had been initiated in Lower Canada through lower mortality. Although it is beyond the scope of this paper to study the demographic transition, we believe that the presence of early signs of its beginning support our claim that population pressures were disappearing. This is because demographic transition is associated with industrialization – something that runs against Malthusian theory. These explanations we propose are merely suggestions at the present time. However, they are plausible and will be easily tested in future papers. We hope at the very least that this new presentation of Malthusian pressures will lead to further research by historians and economists.

Fig. 2.7: Spread of wheat prices between Quebec and Montreal



2.7 Acknowledgements

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3

Business cycles in the economy and in economics: an econometric analysis

by Vadim Kufenko and Niels Geiger

Abstract

Summary. It is sometimes pointed out that economic research is prone to move in cycles and react to particular events such as crises and recessions. The present paper analyses this issue through a quantitative analysis by answering the research question of whether or not the economic literature on business cycles is correlated with movements and changes in actual economic activity. To tackle this question, a bibliometric analysis of key terms related to business cycle and crises theory is performed. In a second step, these results are confronted with data on actual economic developments in order to investigate the question of whether or not the theoretical literature follows trends and developments in economic data. To determine the connection between economic activity and developments in the academic literature, a descriptive analysis is scrutinized by econometric tests. In the short run, the VARs with cyclical fluctuations point out multiple cases where economic variables Granger-cause bibliometric ones. In the long run, the fractionally cointegrated VARs suggest that many bibliometric variables respond to economic shocks. In the multivariate framework, the Diebold–Mariano test shows that economic variables significantly improve the quality of the forecast of bibliometric indices. The paper also includes impulse-response function analysis for a quantitative assessment of the effects from economic to bibliometric variables. The results point towards a qualified confirmation of the hypothesis of an effect of business cycles and crises in economic variables on discussions in the literature.

Keywords: Bibliometric analysis · Business cycle theory · Economics · Fractional cointegration

3.1 Introduction

In the literature on the history of economic thought, it is sometimes pointed out that not only does economic development go through business cycles, but that developments in theory may be of a cyclical nature, or at least contain some cyclical elements, as well (see e.g. Kurz, 2006). Merging the two lines of thought together, i.e. thinking about a possible cyclicality in and of business cycle theory, immediately brings some intuitively appealing examples to mind: Keynes's *General Theory* keynes1936thegeneral, e.g., was published shortly after the onset of the Great Depression and initiated increased interest in analysing business cycles from a new perspective – and has, at least according to casual observations, experienced renewed interest over the past years of the 'Great Recession'. Indeed, numerous examples can be found in the literature which draw a causal link between economic crises, and the frequency of discussions of these and related events. However, so far, those discussions have mostly been unsystematic, casual, and almost exclusively without any actual quantitative reference. The present paper aims to fill this gap by quantitatively and econometrically answering the research question of whether or not the economic literature on business cycles is correlated with movements and changes in actual economic activity.

The analysis begins with a short overview of related literature in two fields: work which discusses the cyclicality and connection to business cycles and crises of economic literature, and bibliometric studies. The following section then contains the core of the empirical analysis. First, the data used and methods employed – both for the bibliometric and econometric analyses – are laid out in detail. Results are subsequently presented and discussed. The latter will also put the results into perspective, theoretically analyze their implications, highlight additional findings, and furthermore discuss caveats. The paper then concludes with a summary of the results.

3.2 Theoretical background and related literature

In his paper on "Cycles in the history of economic ideas" (own translation), Neumark (1975, p. 257 f.) argues that the overall development of economics is of a cyclical nature and not following a straight upward trend towards ever improved new approaches (also see Kurz, 2006). This rather general observation covering various fields of economics overall gains a very peculiar interpretation within the context of discussions of business cycles and crises. Here, a similar argument can be put into perspective of actual economic developments, namely that specific notions and ideas resurface in conjunction of particular policy issues and problems over the course of a business cycle, e.g. unemployment during crises and downswing phases.

Expressions such as "panics produce texts" (see Fabian, 1989, p. 128) imply not only a cyclicality in the literature *per se*, but also one that is correlated with real economic developments. There is also an intuitive appeal to a causality behind this link: Economic crises and recessions produce an increased interest in the discussion of said events, because obviously, the necessity of dealing with them – e.g. by developing relevant policies – is more urgent than it is at tranquil economic times. Therefore, for example, already John Mills (1868, p. 11), in an article presenting his own analysis of cycles and panics, had observed that "every commercial crisis occurring in this country is promptly followed by a literature of pamphlets". Similarly, Aftalion (1913, 289 f.) argues that countless articles appear with every crisis, an observation which was shared a decade later, with the additional experience of yet another crisis, by Richter (1923, p. 153). Another ten years later, Durbin (1933, p. 17) asked for caution when dealing with theories arising in these circumstances, for despite potentially being wrong, they might gain ground given the particular context.[1] It is also straightforward to identify some particularly important examples of theories emerging in context of such events, e.g. Fisher (1932) and Keynes (1936). Concerning the upswing, set into tranquil economics times and shortly before the onset of what has soon afterwards been labelled the 'Great Recession', Lucas (2003, p. 1) claimed that "the central problem of depression prevention has been solved".

Whatever the work cited so far argued about a potential cyclicality in the literature, it has done so on the basis of qualitative readings of academic work and anecdotal examples. In general, bibliometric analysis is a very recent topic indeed in the history of economic thought.[2] Considering the present paper's research interest, there is one previous work on both the bibliometrics of business cycle and crises theory and their connection to economic history, namely a study by Daniele Besomi (2011). In the appendix and introducing discussion of that article, Besomi (2011, pp. 113–117) documents the cumulated absolute frequencies of the titles of different kinds of contributions (journal articles, books, pamphlets, etc.) from various sources, most notably JSTOR and EconLit, but also the author's own assembled records for earlier decades, which contain terms related to crises and business cycles. The terms themselves are identified based on a comprehensive study (which constitutes the larger part of the article) of the respective literature. In a next step, Besomi (2011, p. 55 ff.) subsequently discusses these numbers, with a specific interest in the question of whether or not "panics produce texts", i.e. whether the discussion of economic crises and business cycles is more prevalent during hard times of economic distress. By reference to a number of different

[1] See Besomi (2011, p. 55 f.) for more detail on these references.

[2] For example, see Cardoso et al. (2010), Diamond (2009), Geiger (2014) and Kim et al. (2006). Also see Beckmann and Persson (1998) and Cahlik (2000) for general bibliometric work related to economics.

works, Besomi (2011, p. 56) notes that this thesis of a correlation has been frequently stated, but not quantitatively assessed before his work. However, Besomi's data confirm the casual observation.

Besomi's article clearly is a seminal first step towards providing an organized and structured answer to the question underlying the present paper as well. It provides a nice summary and a general impression, but the method is still fairly unsystematic. Two points are of particular concern: First of all, Besomi discusses only absolute, not relative frequencies. This may be sufficient for a comparison of subsequent years, but for observations over longer time periods, especially over the past century in which the body of academic literature has expanded greatly, there is a substantial risk of systematic errors. As long as the reference group is not included explicitly in a quantitative manner as well, the data cannot be detrended accurately. Furthermore, concerning the connection between economic and bibliometric data, Besomi's approach here is entirely anecdotal, referring to individual historical examples of economic crises without using actual available data and applying statistical methods or running any econometric tests. Besomi is, of course, aware of these shortcomings (see, for example, 2011, p. 118 f.n.). Still, they should be pointed out because they illustrate clearly what the present paper contributes in extension of and going beyond previous work on the topic: it improves on the method of inference, especially concerning the connection between economic and bibliometric data. Furthermore, whereas the empirical documentation constitutes only a small part of Besomi's long article, the present paper is fully dedicated to this analysis.

3.3 Empirical analysis

The following subsections illustrate the empirical strategy, employed data, and main empirical findings of this paper. An analysis which embeds these results in a theoretical context subsequently follows in the discussion.

3.3.1 Method and data

In order to answer the present paper's research question, i.e. whether the history of business cycle theory is in itself cyclical, and whether these movements are related to actual economic developments, two steps of analysis will be made. The first is a bibliometric study of trends in economic research with comprehensive data reaching back well into the second half of the nineteenth century. Following an overview of the bibliometrics, the economic data used are outlined. The subsection closes with a summary of the econometric methods applied.

Bibliometrics

Since the present paper is concerned with broad developments, not just particular works of individual authors, it concentrates on an analysis of frequencies of central notions. That is, the bibliometric data used are numbers and relative amounts of items in the (English) academic journal literature which feature a certain term at least once in the text. The terms searched for are those central to business cycle and crises theory identified by Besomi (2011). Bibliometric time series for these are constructed using data from JSTOR's 'Data ForResearch' (DFR, http://dfr.jstor.org/) tool.

Dating back to the second half of the nineteenth century, JSTOR archives over two hundred periodicals in its 'Economics' subject category, and even more in its 'Business and Economics' subject group category (which includes the former). All the documents are digitalized with optical character recognition, allowing for full-text searches by DFR, which can be restricted by different categories. The following analysis is performed for research articles in journals (i.e. excluding book reviews, editorial items, etc.). This is in order to analyze a fairly homogeneous body of literature, and one that represents the majority of the most relevant work, especially in the more recent decades.[3] JSTOR also includes the large majority of high-ranked journals (according to the RePEc Aggregate Ranking, http://ideas.repec.org/top/top.journals.all.html). The underlying data therefore constitute a very large sample of the full population of relevant research in economics journals. It should be noted that JSTOR's archive is less comprehensive than the American Economic Association's Econ Lit database, but given DFR, it is far more suitable for full text searches of key terms and a subsequent identification of the relevant numbers.

[3] This also excludes books, whether miscellanies or monographs. If economics became more article- and less book-oriented, especially since the nineteenth century, this could imply the risk of systematically wrong assessments of the earlier decades of the time frame observed here, especially since the sample size for the nineteenth century is still fairly small. However, for a key term analysis (in contrast to a citation analysis, where important individual sources might be left out when not including books), this should pose no major problems, as long as content in books does not systematically employ different key terms from journal articles when discussing the same issues – an assumption which seems plausible. Still, it should be pointed out that in one respect, therefore, the present analysis is less comprehensive than that of Besomi (2011): it includes only research articles, no other items. However, this also makes the sample used here more consistent, since the other items Besomi (2011) uses are not available in a comprehensive manner similar to journal archives.

Following Besomi (2011), data are gathered for 14 key notions.[4] The DFR search terms used are as follows: 'bubble', '"business cycle"', '"business cycle" OR "trade cycle"'(further also 'BCTC'),[5] 'crisis', 'cycle', 'depression', 'distress', 'embarrassment', 'fluctuations', 'glut', 'panic', 'prosperity', 'recession', 'stagnation' and '"trade cycle"'. With the search parameters as seen here, all journal articles which include at least one of the terms anywhere in the document are counted.

It is important to highlight that these terms bear different theoretical connotations. For example, there are those referring to the general phenomenon ('business cycle'), whereas others highlight a particular point ('crisis') or a phase ('depression', 'prosperity', 'recession'). Furthermore, it is also possible that the terms' specific meanings have changed over time. To capture such an evolution, a semantic analysis of the occurrences would be warranted, which could highlight, for example, which terms the particular key notions most frequently appeared in conjunction with, etc. Arguably, 'depression' may bear somewhat different implications in 1920 than in 2000. However, this is a further question, and it is not analysed in detail here, albeit touched upon in the discussion. The focus in the present paper is on notions and their frequencies, without an in-depth analysis of what these may actually mean (on this issue, also see Besomi, 2011). Nonetheless, to also capture the relative importance of, respectively discussions on the matter in general, index values are compounded and included in the analysis as well. Two indexes which depict relative frequencies of papers containing at least one of the respective terms are constructed: a "downswing" index which contains 'crisis', 'recession, and 'depression', and an "overall index" which features all terms. In total, therefore, searches are conducted for 16 strings.

To provide just a short impression of the numbers, for the time frame 1850–2010, there are just over 140,000 journal articles in the 'Economics', and over 600,000 in the 'Business and Economics' categories. Since the items are not spread evenly over time, the following analysis works with relative numbers, i.e. the percentage of articles which contain a particular term (such as 'business cycle') relative to all articles in the comparison group (items in 'Economics' and 'Business and Economics' per corresponding year), based on own calculations. That is, if the relative frequency of 'crisis' is $x\%$ in a given year, then $x\%$ of all articles in the respective category for that year contained the word at least once in the text. Of course, such a method of counting does not differentiate – as a proper and informed reading of

[4] One of the terms Besomi (2011) lists, namely 'confidence', is left out here. This is because results for 'confidence' can be expected (and indeed turn out) to be less reliable, since any econometric paper reporting confidence levels on its results will contain the term, no matter which topic it discusses.

[5] This is in order to account for the fact that especially in British literature, 'trade cycle' had been the term of choice describing the same concept for a long time, e.g. in Keynes (1936) and Hicks (1950).

an article could – between how intensely a topic was discussed, with which intention this may have been done, whether a contribution was purely theoretical etc. These shortcomings are analyzed in more detail in the discussion.

Economic variables

In the present paper, United States data are used in order to gauge economic activity. This introduces an element of inaccuracy, since obviously, economists – especially those from other countries – are concerned with more than just US developments. Nonetheless, it seems a reasonable approximation to use data for the world's largest and leading economy (throughout almost all of the time frame for which reliable data are available), especially when working with a body of mostly English literature.

As indicators for macroeconomic activity, time series for real GDP per capita (1871–2012), the unemployment rate (1948–2012), gross private domestic investment (1929–2012), the consumption price index (1851–2012), the S&P stock market index (1871–2012), and a measure of bankruptcy rates are included. Table 3.1 lists all these variables and also the range they cover. The data on income, investments, unemployment and industrial production are taken from the FRED.[6] CPI data are from the long series of Officer and Williamson (2015). The data on the stock market S&P composite index are taken from Shiller (2015) and the bankruptcy rates are taken from Garrett (2007).

Table 3.1: Economic variables

Economic stationary cycles	Description	Time frames
cLNRINCOME	Log of real GDP per capita	1871–2012
cUN	Unemployment rate	1948–2012
cLNINVEST	Log of real gross private domestic investment, Index 2009=100	1929–2012
cLNPROD	Log of the industrial production index, Index 2007=100	1919–2012
cLNCPI	Log of consumption price index, Index average 1982–1984=100	1851–2012
cLNSP	Log of the S&P composite index	1871–2012
cLNBANKR	Log of bakruptcy rates per 1000 capita	1900–2005

Econometric methods

We apply a broad range of econometric tools to test bivariate and multivariate hypotheses in the short and long run: Cointegration and fractional cointegration tests are focused on the long-run relation between the bibliometric and economic

[6] Retrieved on April 22, 2015 from FRED, Federal Reserve Bank of St. Louis https://research.stlouisfed.org/fred2/series/CFMMI/.

variables. Vector autoregressions (VAR) and fractionally cointegrated vector autoregressions (FCVAR) are used for causal inference. Testing the quality of forecasts shows us whether adding economic variables to the intrinsic forecast of the bibliometric variables improves the quality of the forecasts. In addition, we apply white noise tests to ensure the quality of the models.

We first test the stationarity of all variables, both bibliometric and economic, by means of the Augmented Dickey-Fuller test with Generalized Least Squares (further ADF GLS) as in Elliott et al. (1996). From the test results it follows that all of the bibliometric and economic variables can be regarded as random walks and need to be transformed. Before the transformation, we apply the Johansen cointegration test (Hamilton, 1994; Johansen, 1988, 1991) to check if there exists cointegration between the variables. Additionally, we apply the test for fractional cointegration as in Jones et al. (2014) and MacKinnon and Nielsen (2014). According to the standard Johansen (1991) cointegration test, the bibliometric variables are not cointegrated with any of the economic ones and therefore we can apply the VAR framework, as in Hamilton (1994, Chpt. 11). However, for the pairs of variables which are fractionally cointegrated, the FCVAR framework as in Johansen (2008) and Johansen and Nielsen (2012) is a better specification. The FCVAR estimation and fractional differencing is performed with the "FCVAR" Matlab package (see Nielsen and Popiel, 2015). Combining VARs and FCVARs allows us to conduct analysis for the short and long run. The transformation to achieve stationarity is performed with the help of the Kalman filter as in Petris et al. (2009, pp. 51–62). We use the "dlm" package (Petris, 2010) and set a first order polynomial model for filtering. The parameters for the filter are estimated with the maximum likelihood function. The Kalman filter yields stationary cyclical fluctuations, indicated with a "c" before the respective variable name, which are used in the further analysis. Consequently, for the fractionally differenced variables in the FCVARs we use a "d" prefix. Causal inference is preformed in both frameworks.

As for the VARs, once the analysis is conducted we derive the impulse-response functions (IRF) and perform the Granger-causality test, as in Granger (1969). Finally, we check that the residuals of our models are white noise with the Portmanteau Q test as in Ljung and Box (1978). We formulate our model according to Granger (1969, p. 431):

$$\begin{aligned} Y_t &= \beta_0 + \sum_{j=1}^{m} a_j Y_{t-j} + \sum_{j=1}^{m} b_j X_{t-j} + e_t \\ X_t &= \theta_0 + \sum_{j=1}^{m} c_j Y_{t-j} + \sum_{j=1}^{m} d_j X_{t-j} + \eta_t \end{aligned} \tag{3.1}$$

Where Y_t denotes cyclical fluctuations in the economic variables; X_t denotes cyclical fluctuations in bibliometric variables; β and θ denote constants; a, b, c, d denote coefficients for the respective lags and variables; e_t and η_t are error terms and $t - j$ is the lag operator. The optimal lag length is determined for each case with the help of AIC, HQIC and SBIC according to the parsimony principle.

For the FCVARs, similar procedures of lag selection and white noise tests are applied, namely the AIC and BIC criteria and the Portmanteau Q test. In case of the FCVARs, after estimating the model, we apply the test on the long-run exogeneity similar to Jones et al. (2014, p. 1100). The FCVAR is formulated as in Johansen and Nielsen (2012, p. 2668):

$$\Delta^d X_t = \Delta^{d-b} L_b \alpha \beta' X_t + \sum_{i=1}^{k} \Gamma_i \Delta^d L_b^i X_t + \varepsilon_t \tag{3.2}$$

where Δ^d is the fractional difference operator; L_b is a lag operator; $\alpha\beta'$ are the coefficients for the cointegrating vector; Γ_i are the coefficients for the fractionally differenced part, and ε_t t is the error. It is important to note that Eq. 3.2 is expressed in a compact form, and in a FCVAR X_t are the series of interest: bibliometric or economic.

This procedure resembles Granger causality tests and is related to the adjustment parameter α (for details see Johansen and Nielsen, 2012, p. 2669): if a bibliometric variable is not long-run exogenous, then it responds to long-run disequilibrium errors in the cointegration relation between the given bibliometric and economic variable.[7] Thus, the bibliometric variable responds to shocks on the economic one. We test the reverse as well.

A short note should be made on the tests. The Granger causality test is a special case of causal inference, which represents a statistical test of the significance of the VAR coefficients. As Granger (1969, pp. 428–429) notes, this type of causality emerges if certain variables help to predict (or help to improve the forecast of) the future values of others. Applied to our paper, the null hypothesis of the test can be formulated in the following way: economic variables Y_t do not Granger-cause bibliometric ones X_t. This means that if Granger causality from the economic variables to the bibliometric ones exists, that is if we reject the null hypothesis and assume the possibility of the existence of Granger causality, then the current economic situation helps to predict the future bibliometric series. Thus, the concept of Granger causality should be treated in a technical manner, rather than philosophical; it does not yet come with a theoretical argument to explain potential causalities. In order to put the results in a general context and allow

[7] The test on the long-run exogeneity is carried out analogously to Jones et al. (2014, p. 1100) with a 5 % benchmark. The causal inference in cointegrated systems is not straightforward and a standard Wald test as in the case of Granger causality may be problematic (for the discussion see Mosconi and Giannini, 1992). However, the above-mentioned testing procedure allows us to perform long-run inference regarding the responses of bibliometric variables to economic shocks.

for a more comprehensive discussion, Granger causality tests are also performed for the opposite direction, i.e. from bibliometric variables to economic data with the null hypothesis changed respectively. A similar logic is applied to testing the long-run exogeneity in the FCVAR framework. In this case, however, the null hypothesis is that the variable is long-run exogenous and thus does not respond to disequilibrium errors (e.g., economic shocks).

The last tool employed is the Diebold and Mariano (1995) test which offers a multivariate framework to validate our bivariate results. The setup of the Diebold–Mariano test (employing the functions by Baum, 2003) applied in our paper can be considered as a multivariate Granger causality test based on a VAR framework. We construct two forecasting models: an intrinsic forecast of a bibliometric index with five lags and an intrinsic plus economic forecast. The latter includes five respectively all seven economic variables (cLNRINCOME, cUN, cLNINVEST, cLNPROD, cLNCPI, plus cLNSP and cLNBANKR). This test is designed to answer the question of how the inclusion of economic variables to the intrinsic forecast of bibliometric indices contributes to the forecasting quality: If the economic forecast is better than the intrinsic one, then the economic variables indeed help to predict changes in bibliometric indices.

3.3.2 Empirical results

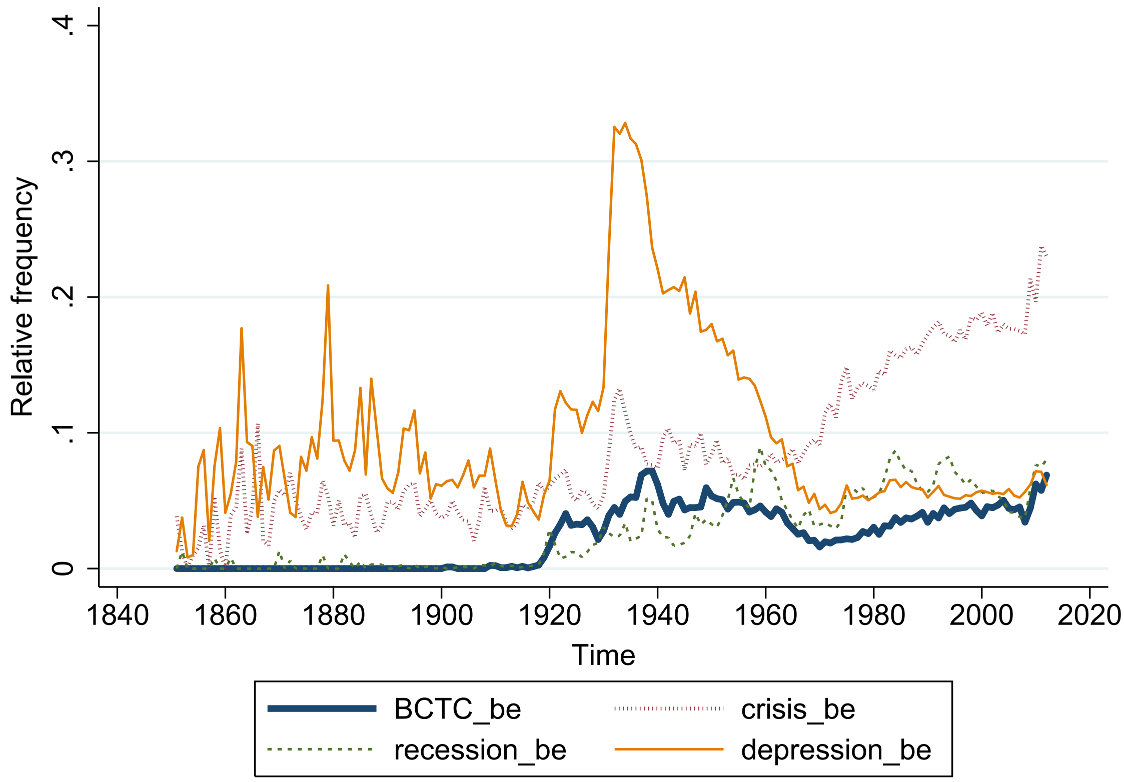
Bibliometric results – descriptive overview

Figure 3.1 provides a general impression of the bibliometric data and respective first results. It displays the relative frequencies of the four arguably most relevant search terms for papers within JSTOR's 'Business and Economics' category, namely 'BCTC' (bold, dark blue), 'crisis' (dotted, red), 'recession' (dashed, green), and 'depression' (thin, yellow) from 1850 to 2012. Some characteristics of these time series immediately catch the eye. For example, the terms 'crisis' and 'depression' have already been in frequent use much longer than the other two. The series for 'BCTC' and 'recession' have been without breaks (i.e. years with no paper featuring either term) since 1909 and 1907 respectively, and, overall, are closer to one another than to the two older time series. A closer look at the 'BCTC' series further reveals the relative importance of 'business cycle' and 'trade cycle' respectively (not displayed in the figure): 'business cycle' has been the far more frequent term overall and throughout, appearing in over eight times as many papers. The frequency of 'trade cycle' peaked in the late 1930s and early 1950s, and then diminished. In the 2000s, only about 0.1% of all journal articles contained the term, whereas 'business cycle' appeared in about 4.5%.

When looking at the 'recession' line, marked fluctuations are evident. Around every ten years, there is a pronounced peak in the series. Overall, though, these fluctuations are around a fairly steady, slightly rising trend. With 'BCTC', on the other hand, there are less pronounced fluctuations, but a clear shift in trends: From the 1940s until around 1970, the relative frequency declined, and then slowly rose again, reaching similar levels to the late 1930s around 2010.

Comparing these two lines to the remaining two allows for further interesting observations. First of all, for almost the whole period, both 'depression' and especially 'crisis' appeared more frequently than the other two. Both had peaks in the early 1930s (whereas 'BCTC' and 'recession' peaked in the late 1930s). The relative frequency of 'depression' steadily declined from the immense height of over 30% per year in 1932–1937 to just around 5–6% in the 1970s and following decades, i.e. on a level with 'BCTC' and 'recession' in the most recent years. On the other hand, the relative frequency of 'crisis' has steadily, albeit with some notable ups and downs along the movement, increased since the 1970s.

Fig. 3.1: Relative frequencies of selected bibliometric variables.



Business cycles in the economy and in economics

Before conducting the bivariate analysis, we perform cointegration tests for long-run inference. According to the ADF GLS test all of the variables are not stationary and therefore we apply the Kalman filter to obtain stationary bibliometric and economic cycles for further analysis after the cointegration tests. The Johansen (1991) cointegration test results suggest no cointegration (see Table 3.8) between the economic and the bibliometric variables. Additionally, we do not find cointegration between the bibliometric variables either. The absence of cointegration according to the Johansen (1991) test does not exclude the possibility of fractional cointegration as in MacKinnon and Nielsen (2014). In Table 3.9 we report the results of the fractional cointegration test: The highest number of cointegrated relations between bibliometric and economic variables can be found for the SP index, CPI, industrial production and real investments for 'Business and Economics' and for industrial production and CPI for 'Economics'. We can transform the variables which do not exhibit any kind of cointegration, and apply the VAR framework. However, for the fractionally cointegrated variables, the FCVAR specification is more appropriate.

In the following, we therefore first report the VAR results for all variables and then, in addition, FCVAR results for the fractionally cointegrated ones. The bivariate modeling allows us to maximize the time frames of our analysis, rather than selecting a uniform time period for all the variables. Selecting a uniform time period for all variables would result in a loss of observations and a higher small sample bias. The number of observations varies from 61 to 156 for different VARs. Even though we strive to use the longest time frames available, we correct our VARs for the small sample size and therefore the Granger causality test and results in Tables 3.2, 3.3, 3.4 and 3.5 already include this adjustment. The lag length for the VARs is selected according to Akaike (AIC), Schwartz Bayesian (SBIC), Hannan-Quinn (HQC) information criteria and the forecasting prediction error as in Nielsen (2001). The optimal lag length of the VARs variates from one to eight lags and the principle of parsimony is applied. Whereas tables 3.2, 3.3, 3.4 and 3.5 contain the Granger causality test results, Table 3.6 reports the Q test for the white noise in residuals. The latter is necessary to filter out results of the models which fail to produce residuals with constant variance and zero mean. We use the 5% benchmark for all the tests applied, including the Q test for white noise. In addition, we differentiate between Granger causality in the direction towards bibliometric variables, instantaneous Granger causality (Granger, 1980, p. 340) and Granger causality in the opposite direction. The formulation of the null hypothesis of the Granger causality test applied in this paper is that economic variables do not Granger-cause bibliometric ones. Therefore, at levels lower than 5% we reject the absence of Granger causality and assume either Granger causality in the direction of bibliometric variables, instantaneous or reverse Granger causality. The white noise Q test applied allows us to accept or reject the null hypothesis that the residuals of our VARs are white noise and have constant variance and zero mean. Values less than 5% benchmark would suggest that the residuals are not white noise and therefore the related results are questionable.

We first document the results related to the literature from 'Business and Economics' (Tables 3.2 and 3.3) and then validate them with the help of the sample from the 'Economics' subset only (Tables 3.4 and 3.5). Let us start with highlighting the Granger causality from economic variables to the bibliometric ones and therefore investigate whether the economic "panic" indeed produces related scientific works ("texts"). The p values from Table 3.2 point out Granger causality for the main economic variables of interest. It appears that on the 5% level, we can assume that the cyclical fluctuations of real income per capita Granger-cause bibliometric data on 'panic', 'stagnation' and the "overall" index; cyclical fluctuations of unemployment Granger-cause 'fluctuations', 'business cycle' and 'prosperity'; cyclical fluctuations of real investments Granger-cause the most bibliometric variables, namely 'fluctuations', 'business cycle', 'crisis', 'cycle', 'panic', 'stagnation' and the "overall" index; cyclical fluctuations of industrial production Granger-cause 'BCTC' and 'recession'; cyclical fluctuations of CPI Granger-cause 'business cycle'. From Table 3.3 with additional economic variables we find that the cyclical fluctuations of the S&P composite index Granger-cause bibliometric data on 'crisis', 'depression' and the "downswing" index. The cyclical fluctuations of bankruptcy rates per 1000 capita Granger-cause only fluctuations in literature using the term 'bubble'.

Tables 3.4 and 3.5 focus only on the literature from the 'Economics' category and validate our hypothesis on the relation between economic and bibliometric variables: cyclical fluctuations of real income per capita Granger-cause 'distress', 'panic' and the "overall" index; cyclical fluctuations of real investments Granger-cause 'business cycle', 'crisis', 'cycle', 'panic', 'prosperity' and the "overall" index; industrial production Granger-causes 'BCTC', 'business cycle', 'cycle' and 'stagnation'; CPI Granger-causes 'embarrassment'. For the additional variables, the results from the 'Economics' category validate exactly the same causalities as for 'Business and Economics', obtained in Table 3.3. In general, for the 'Economics' literature we were able to find 18 incidents of Granger causality from economic variables to bibliometric ones, whereas in the 'Business and Economics' category we found 19 such incidents.

Instantaneous Granger causality can be found for the following cyclical fluctuations in the 'Business and Economics' category: unemployment and 'BCTC', 'cycle' and 'recession'; real investments and 'BCTC', 'depression' and 'distress'; industrial production and 'business cycle' and 'cycle'. One has to note that this instantaneous phenomenon is rare, compared to the Granger causality from economic to bibliometric cycles.

Tables 3.4 and 3.5 show similar instantaneous Granger causalities for the 'Economics' literature: between the cyclical fluctuations of real income per capita and 'crisis'; unemployment and 'BCTC', 'business cycle', 'cycle' and 'recession'; real investments and 'depression' and 'distress'; industrial production and 'bubble' and 'recession'; CPI and 'recession'. The share of instantaneous Granger causalities in the sphere of 'Economics' is slightly higher compared to 'Business and Economics'.

The opposite direction of Granger causality, i.e. from bibliometric data to economic variables, is also worth mentioning. This phenomenon can be detected for cyclical fluctuations in real income per capita and 'distress', 'prosperity' and the "downswing" index; unemployment and 'stagnation'; investments and 'depression', 'distress'; industrial production and 'bubble'; CPI and 'panic', 'prosperity' and 'stagnation'. From Table 3.3 we find such causality for cyclical fluctuations of the S&P index and 'stagnation' as well as bankruptcy rates per 1000 capita and 'recession'. Finding Granger causality in this direction, i.e. opposed to the one expected, may be surprising, and is discussed in detail in the next section. In Tables 3.4 and 3.5 we find reverse Granger causality for: real income per capita and 'prosperity' and the the "downswing" index; CPI and 'fluctuations'; as well as bankruptcy rates and 'recession'.

All the VARs are checked for stability and they fulfill the related conditions. As seen in Table 3.2, there exists a simultaneous Granger-causality between the cyclical fluctuations of income and bibliometric data on 'fluctuations', however, the white noise test results from cell A9 in Table 3.6 suggest that the residuals from this VAR are not white noise and therefore this Granger-causality test result should be treated with extreme caution. The same applies to A6, E3 and F8. We refrain from reporting the related Granger causality test results due to the fact that the residuals for these VARs are not white noise. Table 3.7 tests the residuals from models related to the 'Economic' literature (from Tables 3.4 and 3.5). Here, A19 and E19 do not pass the test.

The selected IRFs from Fig. 3.2 display simulation results based on our VAR estimation. These simulations show how and how long the literature reacts on economic variables: a positive impulse from unemployment causes a positive reaction of the bibliometric data on 'business cycle', whereas positive impulses from investments, industrial production and the S&P index cause a negative reaction of bibliometric data on 'crisis', 'panic', 'recession', 'BCTC' and 'crisis'. One should note that most of the functions converge after 4–5 steps.

Bearing Fig. 3.2 in mind, one could use the simulated impulses to quantify the impact of economic variables on literature in the sphere 'Business and Economics': a 1% increase of the unemployment rate in the previous year leads to a 0.0266 % points increase in papers using 'business cycle' in the current year; a 1% increase of real investments in the previous year leads to a 0.4339 % points decrease in 'crisis' in the current year; a 1% increase of real investments in the previous year leads to a 0.1116 % points decrease in 'panic' in the current year; a 1% increase of industrial production in the previous year leads to a 0.3189 % points decrease in 'recession' in the current year; a 1% increase of industrial production in the previous year leads to a 0.1544 % points decrease in 'BCTC' in the current year; a 1% increase in the S&P stock market index in the previous year leads to a 0.4415 % points decrease in 'crisis' in the current year. The above-mentioned effects refer to the first year after the impulse and are purely illustrative.

In practice, one could interpret this in a following way: economic variables usually have the strongest impact on the economic literature in the first 1–5 years after the impulse. Obviously, Fig. 3.2 shows only a small number of IRFs, and not even all of the relations for which positive Granger causality results were observed. Their patterns, however, are characteristic, which is why they were selected.

Next, the results for the fractionally cointegrated pairs are reported. The number of cointegrated relations documented in Table 3.9 is substantial, and therefore for the related pairs a FCVAR specification is desirable. The lag selection is performed according to the AIC and BIC criteria. In addition, the same white noise Q test as in the VAR case is conducted and the stability is checked (Tables 3.14, 3.15).

In Tables 3.2, 3.3, 3.4 and 3.5 with the Granger causality test results, cases of fractionally cointegrated variables are marked with square brackets. For those variable pairs, Tables 3.10, 3.11, 3.12 and 3.13 report the long-run exogeneity tests based on the FCVAR estimations. Let us start with the results from 'Business and Economics'. The cases where the bibliometric variable responds to economic shocks and the model passes the white noise tests are: real income per capita and 'recession'; unemployment and 'business cycle' and the "overall" index; real investments and 'business cycle', 'BCTC' and 'distress'; industrial production and 'bubble'; CPI and 'crisis', 'glut' and 'recession'; SP and the "downswing" index. For the 'Economics' category, the figures from Tables 3.12 and 3.13 suggest that the same holds for: industrial production and 'business cycle', 'embarrassment' and 'panic'; CPI and 'crisis', 'embarrassment', 'glut', 'recession' and 'stagnation'; bankruptcy rates per 1000 capita and 'embarrassment' and 'glut'. The results show that bibliometric variables respond to long-run disequilibrium errors and thus, economic shocks.

We also detect cases where both variables are not long-run exogenous, i.e. that both respond to shocks in the other. For 'Business and Economics', the cases where both variables respond to shocks are: real income per capita and 'crisis' and 'fluctuations'; unemployment and 'bubble'; real investments and 'recession'; industrial production and 'recession'; CPI and 'stagnation'; SP and 'cycle'; bankruptcy

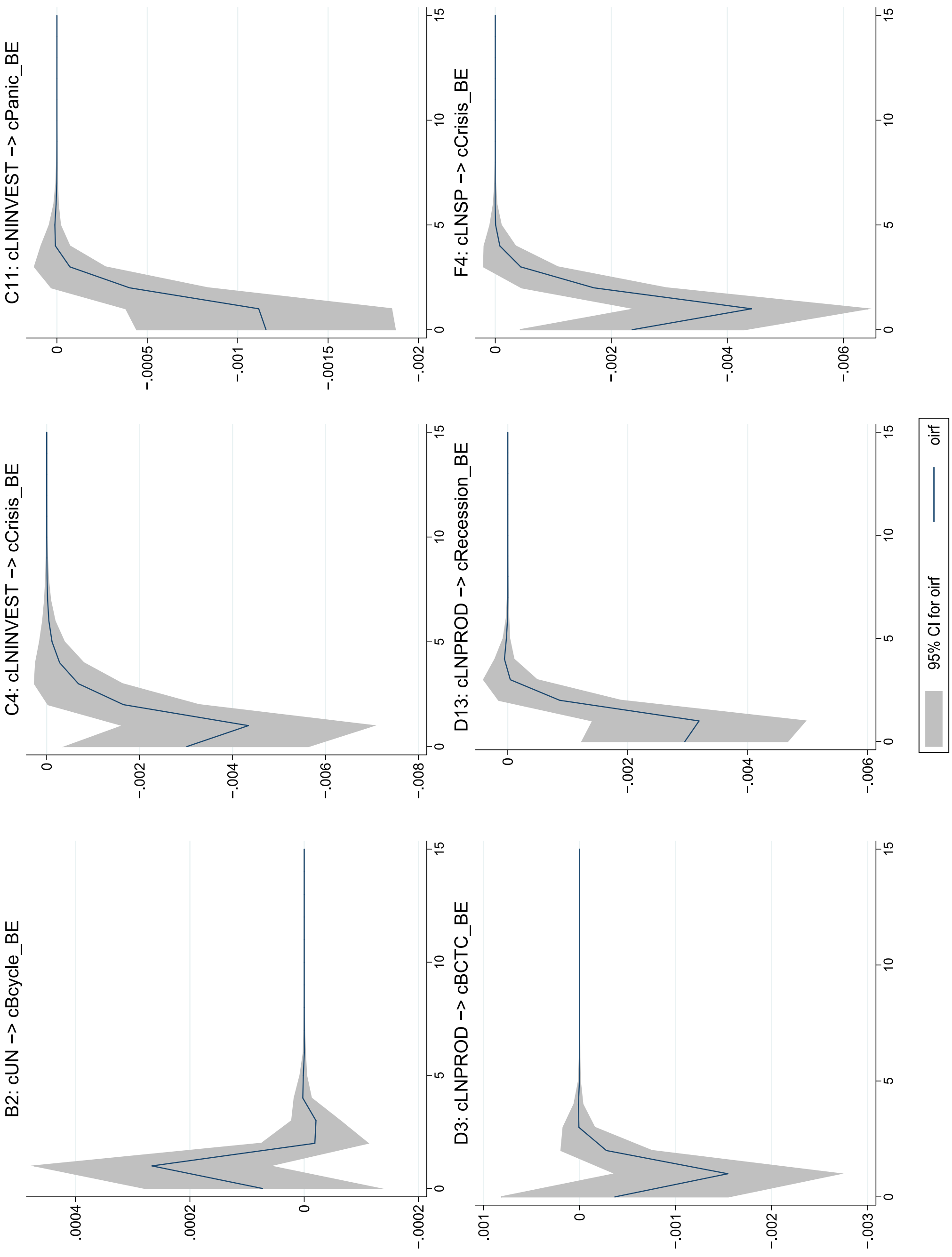


Fig. 3.2: Selected impulse-response functions, for Tables 3.2 and 3.3

rates and 'prosperity'. For 'Economics', such cases are: real income per capita and 'business cycle' and 'cycle'; industrial production and 'recession'; SP and 'cycle'.

A third category includes those cases where the bibliometric variables are long-run exogenous, but the economic variables are not. For 'Business and Economics', these are real income per capita and 'depression'; real investments and 'bubble'; industrial production and the "downswing" and "overall" indices; CPI and 'distress'; SP and 'business cycle', 'distress' and 'recession'. For 'Economics', we find: real income per capita and 'panic'; industrial production and 'bubble'; CPI and 'prosperity'; SP and 'crisis', 'distress', 'recession' and 'stagnation'.

The long-run exogeneity tests after FCVARs resemble the Granger causality results: The first type of cases with bibliometric variables responding to economic shocks prevails, but other cases are present as well.

The last step in our analysis is the multivariate inference with the Diebold–Mariano test., i.e. whether the economic variables taken together can forecast the literature as captured by the "overall" and "downswing" indices. Table 3.16 summarizes the results: we test the quality of the forecasts using two criteria (Mean Square Error, or MSE and Mean Absolute Error, or MAE) and apply the Barlett kernel for the long run variance estimation. All but one test results indicate that the forecast of bibliometric indices using economic variables is of a better quality than the intrinsic forecast, rejecting the null hypothesis of zero difference at the 5 % level. The only exception is the forecast of the "overall" index from 'Economics' using all economic variables. However, in this case, the p value is only marginally higher than the 5 % benchmark. In general it appears that the economic variables significantly improve the quality of the forecasts of bibliometric ones.

3.4 Discussion

It is important to discuss the instantaneous and the opposite Granger causality, found in Tables 3.2, 3.3, 3.4 and 3.5. Regarding the instantaneous Granger causality, we consider this finding as a positive evidence of interaction between the state of the economy and scientific activity. According to Granger (1980, p. 340), such instantaneous phenomena can be related to measurement issues: the frequency of our data is annual, whereas the actual causality may occur at higher frequencies. However, bearing in mind the submission process and the review time for scientific literature, considering the series at an annual level is reasonable (and, at any rate, inevitable, given the availability of data). Furthermore, it can also be pointed out that in most instances of instantaneous causality, the significance level on the direction of bibliometric to economic data is much higher than its opposite. Therefore, it may be argued that the effect in the "expected" direction is more significant.

Nevertheless, we acknowledge the fact that the measurement issue exists and that it can be related to the instantaneous Granger causality found for the abovementioned variables. Another potential explanation would be either an exceptional forecasting quality of the related economic literature, which can capture contemporary trends in the economic data, or the ”production function” of the scientific journals and editors: If, during times of an economic crises and recession, journal editors strive to issue and publish papers as fast as possible while the topics are still relevant, an economic downturn earlier in a year may very well co-occur with many discussions on it later in the year – which, given annual data for both variables, may result in instantaneous Granger causality. Considering the reverse causality, one could speculate and assume that there is a policy or sentiment channel, through which the economic literature can impact the economic variables. In this case we could also assume that economic texts can produce “panics”, or at least certain sentiments which can influence economic activity (see e.g. Soo, 2013). However, one could also leave room for statistical errors and a missing variable bias which leads to such test results. We should reiterate that the “reverse” Granger causalities, as well as the instantaneous ones, are rather rare compared to the Granger causality from economic cycles to bibliometric ones. The reverse causality nonetheless offers a fruitful ground for further research.

Overall, the empirical results in this paper have been in accordance with earlier discussion in the literature and, due to their intuitive appeal, quite compelling. The IRF estimates in particular provide a specific quantitative assessment of the illustrated relations: For example, it was demonstrated that a 1% decrease in industrial production from its trend implies a 0.3189 % points increase in the relative frequency of ‘recession’ in the ‘Business and Economics’ category. Given that this frequency fluctuates between 5%–10% historically, this implies a relative change of 3%–6% in the frequency of ‘recession’ following a 1% change in industrial production. Despite these strong results, it is important to add some caveats concerning the generality and broad applicability of the results, which owe partly to the data used, but also to the details of the results. One major issue which needs to be pointed out is the method of counting articles. As outlined in the section on method and data, any article which contains the particular key term in question at least once anywhere in the text was counted. This means that there is no differentiation between how often the term appears, and in what way the particular notion is qualitatively discussed (which is next to impossible for a broad bibliometric analysis anyway). For example, it might be that the reason behind increased frequencies in the context of crises and recessions are no increased theoretical discussions, but a simple shift in introductions to economic texts, whatever their specific topic, which now begin their discussions with obervations such as “In context of the recent crisis...” or similar. This might also explain why the fluctuations and corresponding peaks in the ‘recession’ time line of Fig. 3.1 are more pronounced than in the 'BCTC' series: When a recession hits, it may very well not be the term 'business cycle' which is used in introductions referring the event, but, instead, 'recession'.

The problem of properly counting items might be avoided if instead of searching for terms anywhere in the document, key terms associated with the documents would be analyzed. JSTOR's DFR contains automatically generated key terms (based on frequencies within the document). If a notion such as 'recession' is featured among these, it is less likely that there is only lip service done to business cycle theory; but it may also happen that a business cycle theory paper might be excluded because of other, more frequent notions among the key terms (for example, the most frequent key terms in the 'Economics' category include such general notions as 'market', 'price' and 'capital'). Further research can help to clarify this issue and contribute to a more precise understanding.

The last point to be discussed is the lag selection procedure. We estimate the optimal lag by AIC, BIC, SBIC and HQIC (where applied) for our VAR and FCVAR models to be consistent. The lag length for the majority of our models is between 1 and 2 periods (i.e. years). However, in some cases the optimal lag length was 4, 5, 6 or 8. A one or two year lag length seems to closely correspond to writing time plus publication delay in economics: Indeed, Björk and Solomon (2013) identify an 18 month delay between the original submission and publication for business/economics journals. A lag length around 6 years, on the other hand, would roughly capture the length of typical business cycles (based on the National Bureau of Economic Research's authoritative timing and dating of US business cycles). Therefore the optimal lag selection based on information criteria covers both situations, which are also both reasonable delays for a reaction of the literature to changes in economic variables: when the variations are driven by publication lags, and when the variations are driven by the business cycle phases.

3.5 Conclusion

The theoretical background in the second section demonstrated that the research question guiding this paper derives from a recurring theme in the economic literature, almost as old as business cycle and crises theory itself. With the availability of digitalized archives of the academic literature, it has become possible to answer such questions quantitatively, i.e. to provide a more specific and detailed analysis of broad trends than the discussion of any individual paper or small set of papers could.

The results generally confirm the theoretically appealing intuition based on observations of current events and anecdotal examples which could be found in the earlier literature, i.e. that business cycle and crises theory (more specifically:

the frequency of its key notions, especially those related to the downswing) is on the rise during economically hard times, and experiences decreasing interest in prosperous times. However, they also point out that this thesis has to be taken with a grain of salt, and that further research will be necessary to get a more detailed understanding of the relation between business cycles in the economy and in economics. After testing the residuals for white noise we find 19 Granger causality incidents from economic variables to bibliometric ones in the field 'Business and Economics' and 18 incidents in the field 'Economics', including notable intersections, which largely validates our hypothesis. In addition, we find incidents of instantaneous and reverse Granger causality, but their share is lower. Another valuable finding is related to the IRFs. These provide quantitative measures of the effects from economic to bibliometric variables, and further allow us to point out that in general the strongest reaction of bibliometric variables on the economic ones takes place within 1–5 years from the initial impulse.

The FCVAR analysis, which was conducted for those cases in which fractional cointegration was found, documents eleven instances where the 'Business and Economics' literature in the long run reacts to economic shocks. In the 'Economics' category, ten such instances were found. Here, too, the number of instances where economic variables responded to bibliometric ones or both responded to one another was lower than for the first category. Finally, the Diebold–Mariano test suggests that in a multivariate framework, the quality of a forecast of bibliometric variables using economic variables is significantly more accurate than a simple intrinsic forecast.

Even though the analysis and results presented in this paper clearly provide a step forward in answering the underlying research question of the cyclicality in business cycle and crises theory, and its connection to actual economic developments, there are still caveats to be kept in mind which were addressed in the discussion. Further research may contribute to clarify these issues. To begin with, the key term analysis may be scrutinized. Furthermore, it is possible to conduct similar analyses as was done for the key terms here, but for citation counts instead of key terms. When taken together, this would allow for a more comprehensive account of the general topic overall, which was not included in the present paper because business cycle and crises theory is such a broad field with such a wide spread (as was evident from the numbers and figures, e.g. in Fig. 3.1) that including more than the terms would have meant going beyond the scope of a single paper. Nonetheless, this demonstrates how many more answers bibliometric research may provide to these research questions.

3.6 Acknowledgements

The authors are grateful for helpful comments by Pedro Garcia Duarte, Harald Hagemann, Johannes Schwarzer and an anonymous referee.

3.7 Appendix

See Tables 3.2, 3.3, 3.4, 3.5, 3.6, 3.7, 3.8, 3.9, 3.10, 3.11, 3.12, 3.13, 3.14, 3.15 and 3.16.

Table 3.2: Granger causality - five variables, category: 'Business and Economics'. Significant results are in bold. Items in square brackets indicate fractal cointegration.

No.	Variables	A) cLNRINCOME		B) cUN		C) cLNINVEST		D) cLNPROD		E) cLNCPI	
	Direction of Granger causality	to literature		to literature		to literature		to literature		to literature	
1	cBubble_BE	0.166	0.1112	[0.5072]	[0.7735]	[0.1345]	[0.5385]	[0.2564]	[0.0223*]	0.7492	0.7422
2	cBcycle_BE	0.7828	0.5048	[0.0012*]	[0.0849]	[0.0004*]	[0.0573]	**0.002***	**0.0473***	**0.028***	0.3631
3	cBCTC_BE	0.2268	0.1937	**0.0088***	**0.0138***	[0.0002*]	[0.0234*]	**0.0095***	0.0609	0.3164	**0.0232***
4	cCrisis_BE	[0.3121]	[0.2084]	[0.6223]	[0.7068]	**0.0083***	0.1188	0.6991	0.1506	[0.6203]	[0.1095]
5	cCycle_BE	0.4789	0.357	**0.0042***	**0.0005***	**0.0039***	0.1259	**0.0015***	**0.0022***	0.4116	0.983
6	cDepression_BE	[0.3539]	[0.0055*]	0.5167	0.5183	**0.0209***	**0.0003***	0.7872	0.6866	0.5085	0.1543
7	cDistress_BE	0.3182	**0.0059***	0.5742	0.7514	[0.0001*]	[0.0038*]	0.443	0.7938	[0.5856]	[0.2993]
8	cEmbarrassment_BE	0.8631	0.3503	0.2807	0.1118	0.2707	0.3298	0.8333	0.912	[0.1768]	[0.9136]
9	cFluctuations_BE	[0.001*]	[0.014*]	**0.0072***	0.5358	**0.0004***	0.545	0.0833	0.7055	0.3245	0.5897
10	cGlut_BE	0.6876	0.0992	0.4509	0.2289	0.2651	0.5942	0.6656	0.9882	[0.0719]	[0.621]
11	cPanic_BE	**0.0006***	0.93	0.4793	0.4722	**0.0193***	0.0731	0.9852	0.453	0.5203	**0.0191***
12	cProsperity_BE	0.3429	**0.0418***	**0.0021***	0.1933	0.07	0.0519	[0.2704]	[0.4323]	0.9882	**0.0006***
13	cRecession_BE	[0.1103]	[0.7009]	**0.0322***	**0.0349***	[0.5005]	[0.0806]	[0.0019*]	[0.0802]	[0.5275]	[0.2202]
14	cStagnation_BE	**0.033***	0.7934	0.5816	**0.0127***	**0.0278***	0.7076	0.1518	0.3251	[0.6654]	[0.0025*]
15	cINDEXdown_BE	0.1694	**0.0279***	0.6508	0.8921	0.3453	0.6195	[0.763]	[0.6401]	0.8109	0.1218
16	cINDEXoverall_BE	**0.0201***	0.2538	[0.1203]	[0.0076]	**0.0164***	0.2967	[0.3053]	[0.4305]	0.8751	0.0212

Significant results are in bold. Items in square brackets indicate fractional cointegration

* 5% benchmark is used; the H0 of the test is that the economic variable does not Granger-cause the bibliometric variable.

Table 3.3: Granger causality – additional variables, category: 'Business and Economics'. Significant results are in bold. Items in square brackets indicate fractal cointegration.

No.	*Variables*	F) cLNSP		G) cLNBANKR	
	Direction of Granger causality	to literature		to literature	
1	cBubble_BE	0.6456	0.7524	**0.0342***	0.3486
2	cBcycle_BE	[0.1155]	[0.8289]	0.87	0.7557
3	cBCTC_BE	0.3541	0.8244	0.9174	0.7761
4	cCrisis_BE	**0.0001***	0.4876	0.6402	0.109
5	cCycle_BE	[0.4336]	[0.307]	0.8044	0.741
6	cDepression_BE	**0.0067***	0.3742	0.9955	0.9617
7	cDistress_BE	[0.6681]	[0.3418]	0.2851	0.7877
8	cEmbarrassment_BE	0.7128	0.6458	[0.6341]	[0.9945]
9	cFluctuations_BE	0.6685	0.4298	0.8462	0.976
10	cGlut_BE	[0.8004]	[0.6807]	0.7577	0.5011
11	cPanic_BE	0.5279	0.5777	0.873	0.9605
12	cProsperity_BE	0.3312	0.3891	[0.9686]	[0.9384]
13	cRecession_BE	[0.4714]	[0.6815]	0.6975	**0.0156***
14	cStagnation_BE	0.0569	**0.0227***	0.5403	0.9869
15	cINDEXdown_BE	[0.0005*]	[0.747]	0.2106	0.6693
16	cINDEXoverall_BE	0.0916	0.539	0.9922	0.5563

Significant results are in bold. Items in square brackets indicate fractional cointegration
* 5% benchmark is used; the H0 of the test is that the economic variable
does not Granger-cause the bibliometric variable.

Table 3.4: Granger causality – additional variables, category: 'Economics'. Significant results are in bold. Items in square brackets indicate fractal cointegration.

No.	*Variables*	F) cLNSP		G) cLNBANKR	
	Direction of Granger causality	to literature		to literature	
17	cBubble_E	0.6072	0.6594	**0.0142***	0.0785
18	cBcycle_E	0.2452	0.8582	0.5683	0.3362
19	cBCTC_E	0.3411	0.642	0.595	0.53
20	cCrisis_E	[0.0001*]	[0.7588]	0.1971	0.4871
21	cCycle_E	[0.2433]	[0.4784]	0.2127	0.2748
22	cDepression_E	**0.0411***	0.7185	0.8839	0.8899
23	cDistress_E	[0.5912]	[0.0861]	0.6929	0.6746
24	cEmbarrassment_E	0.1727	0.7185	[0.996]	[0.9957]
25	cFluctuations_E	0.9262	0.784	0.8927	0.9041
26	cGlut_E	0.7445	0.826	[0.9564]	[0.6006]
27	cPanic_E	0.4888	0.3873	0.5637	0.9737
28	cProsperity_E	0.7887	0.9907	0.6951	0.7775
29	cRecession_E	[0.5907]	[0.5931]	0.4522	**0.0461***
30	cStagnation_E	[0.2055]	[0.2358]	0.6317	0.8316
31	cINDEXdown_E	**0.0186***	0.9754	0.4191	0.3494
32	cINDEXoverall_E	0.2934	0.5387	0.3596	0.543

Significant results are in bold. Items in square brackets indicate fractional cointegration
* 5% benchmark is used; the H0 of the test is that the economic variable
does not Granger-cause the bibliometric variable.

Table 3.5: Granger causality - five variables, category: 'Economics'. Significant results are in bold. Items in square brackets indicate fractal cointegration.

No.	*Variables*	A) cLNRINCOME		B) cUN		C) cLNINVEST		D) cLNPROD		E) cLNCPI	
	Direction of Granger causality	to literature		to literature		to literature		to literature		to literature	
17	cBubble_E	0.2747	0.8894	0.1692	0.4335	0.3747	0.9966	[0.0078*]	[0.0212*]	[0.3836]	[0.0567]
18	cBcycle_E	[0.5348]	[0.572]	**0.0062***	**0.0323***	**0.0181***	0.1914	[0.0006*]	[0.1015]	0.1243	0.2608
19	cBCTC_E	0.327	0.531	**0.0209***	**0.0323***	0.192	0.2	[0.0015*]	[0.0887]	0.2486	**0.0437***
20	cCrisis_E	**0.0131***	**0.0009***	0.1732	0.9596	**0.0346***	0.736	0.1352	0.3482	[0.3269]	[0.2502]
21	cCycle_E	[0.2506]	[0.7059]	**0.0152***	**0.0111***	**0.0421***	0.0714	[0.0013*]	[0.0522]	0.8457	0.0364
22	cDepression_E	[0.449]	[0.0081*]	0.9535	0.9616	**0.0034***	**0.0027***	0.4925	0.833	0.5463	0.7911
23	cDistress_E	**0.0021***	0.82	0.2633	0.7842	**0.0003***	**0.0372***	0.0942	0.7605	0.7912	0.2001
24	cEmbarrassment_E	0.6055	0.0777	0.284	0.9819	0.7205	0.4771	[0.4799]	[0.6837]	[0*]	[0.0943]
25	cFluctuations_E	0.15	0.1259	0.1274	0.0726	0.1361	0.6274	0.1329	0.5705	0.1414	**0.046***
26	cGlut_E	0.5896	0.5994	0.699	0.2268	0.5791	0.7645	0.9466	0.5249	[0.4739]	[0.5259]
27	cPanic_E	[0.0023*]	[0.3632]	0.9221	0.1607	**0.001***	0.8315	[0.5987]	[0.1074]	0.8385	0.1747
28	cProsperity_E	0.9963	**0.0006***	0.1193	0.6854	**0.047***	0.1086	0.4439	0.2105	[0.6588]	[0.409]
29	cRecession_E	0.1241	0.53	**0.0314***	**0.0478***	0.5609	0.3923	[0.0127*]	[0.0474*]	[0.0146*]	[0.0056*]
30	cStagnation_E	0.0804	0.6801	0.2186	0.0714	0.5344	0.4595	**0.0441***	0.4289	[0.4672]	[0.5598]
31	cINDEXdown_E	0.1564	**0.0271***	0.1435	0.6025	0.2857	0.6445	0.1258	0.7409	0.8702	0.743
32	cINDEXoverall_E	**0.0304***	0.2616	0.063	0.1863	**0.0023***	0.3381	0.0505	0.955	0.9956	0.7726

Significant results are in bold. Items in square brackets indicate fractional cointegration
* 5% benchmark is used; the H0 of the test is that the economic variable does not Granger-cause the bibliometric variable.

Table 3.6: Portmanteau Q test of the residuals, category: ‘Business and Economics’. Significant results are in bold.

No.	A	B	C	D	E	F	G
1	0.354	0.3605	0.98	0.9601	0.3253	0.9657	0.8786
2	0.4216	0.835	0.9533	0.9764	0.7992	0.7979	0.6685
3	0.5559	0.6385	0.9279	0.9862	**0.0272***	0.454	0.5265
4	0.2741	0.8396	0.1503	0.9419	0.8452	0.2335	0.7556
5	0.2644	0.376	0.9631	0.972	0.8871	0.2065	0.5372
6	**0.0037***	0.8212	0.991	0.9751	0.685	0.4442	0.542
7	0.1946	0.742	0.8531	0.9212	0.4582	0.3448	0.5466
8	0.7991	0.9748	0.2234	0.8069	0.0626	**0.0157***	0.803
9	**0.0415***	0.956	0.8913	0.9144	0.842	0.2693	0.5259
10	0.2547	0.2718	0.9145	0.9272	0.269	0.5673	0.6336
11	0.2384	0.5523	0.5669	0.9462	0.562	0.2481	0.5636
12	0.2596	0.5027	0.9939	0.974	0.8931	0.2533	0.5625
13	0.1667	0.6252	0.9521	0.9878	0.9876	0.4483	0.7793
14	0.2379	0.9738	0.1695	0.966	0.4079	0.4641	0.4844
15	0.1366	0.612	0.1525	0.9359	0.1857	0.2606	0.7095
16	0.1753	0.5057	0.2596	0.9463	0.313	0.2751	0.5877

Significant results are in bold
* 5% benchmark is used.

Table 3.7: Portmanteau Q test of the residuals, category: 'Economics'. Significant results are in bold.

No.	A	B	C	D	E	F	G
17	0.2438	0.3824	0.1569	0.9607	0.1575	0.5093	0.7823
18	0.1317	0.324	0.9831	0.9432	0.5207	0.9385	0.6874
19	**0.0108***	0.3214	0.9896	0.9607	**0.0202***	0.7684	0.4946
20	0.2809	0.33	0.1493	0.9385	0.2021	0.2509	0.5207
21	0.2505	0.1775	0.9748	0.932	0.3242	0.2165	0.6262
22	0.1907	0.9513	0.9908	0.9308	0.3097	0.2468	0.5508
23	0.2296	0.3096	0.871	0.9335	0.3017	0.4269	0.5119
24	0.6047	0.7855	0.7109	0.9793	0.0607	0.562	0.5727
25	0.2983	0.2362	0.9552	0.9099	0.5187	0.2572	0.4963
26	0.2026	0.3059	0.8872	0.924	0.2345	0.6045	0.651
27	0.0595	0.152	0.9455	0.9481	0.4035	0.2761	0.5723
28	0.3568	0.3319	0.9675	0.8753	0.3105	0.2466	0.6015
29	0.1469	0.4525	0.9593	0.9445	0.0602	0.4387	0.7223
30	0.2542	0.3195	0.9958	0.9384	0.3089	0.2061	0.6464
31	0.2386	0.2983	0.1554	0.9329	0.2814	0.2454	0.6195
32	0.2139	0.3383	0.9778	0.9284	0.3174	0.2441	0.584

Significant results are in bold

* 5% benchmark is used.

Table 3.8: Johansen cointegration test

Cointegration rank		
Variable	‘Business and Economics’	‘Economics’[a]
LNRINCOME	0	0
UN	0	0
LNINVEST	0	0
LNPROD	0	0
LNCPI	0	0
LNSP	0	0
LNBANKR	0	0

[a] Excluding ‘stagnation’ due to estimation issues

Table 3.9: Fractional cointegration test

Cointegration rank		
Variable	‘Business and Economics’	‘Economics’
LNRINCOME	4	4
UN	4	0
LNINVEST	5	0
LNPROD	5	7
LNCPI	6	7
LNSP	6	5
LNBANKR	2	2

Table 3.10: FCVAR long-run exogeneity test - five variables, category: 'Business and Economics'. Significant results are in bold.

No.	*Variables*	H) LNRINCOME		I) UN		K) LNINVEST		L) LNPROD		M) LNCPI	
	Long-run exogeneity	Biblio	Economic	Biblio	Economic	Biblio	Economic	Biblio	Economic	Biblio	Economic
33	dBubble_BE			**0.001***	**0.0384***	0.0814	**0.0023***	**0.0094***	0.9		
34	dBcycle_BE			**0.000***	0.1047	**0.0020***	0.8131				
35	dBCTC_BE					**0.0010***	0.3262				
36	dCrisis_BE	**0.0020***	**0.000***	0.1674	0.0576					**0.000***	0.0775
37	dCycle_BE										
38	dDepression_BE	0.1207	**0.000***								
39	dDistress_BE					**0.0025***	0.0913			0.8498	**0.000***
40	dEmbarrassment_BE									**0.000***	0.6352
41	dFluctuations_BE	**0.0500***	**0.000***								
42	dGlut_BE									**0.000***	0.2537
43	dPanic_BE										
44	dProsperity_BE							0.0526	0.1407		
45	dRecession_BE	**0.0159***	0.0728			**0.0015***	**0.014***	**0.002***	**0.0195***	**0.000***	0.6981
46	dStagnation_BE									**0.000***	**0.0193***
47	dINDEXdown_BE							0.7727	**0.000***		
48	dINDEXoverall_BE			**0.000***	0.0772			0.144	**0.001***		

Significant results are in bold
* 5% benchmark is used; the H0 of the test is that the given bibliometric or economic variable is exogenous in the FCVAR model

Table 3.11: FCVAR long-run exogeneity test - two variables, category: 'Business and Economics'. Significant results are in bold.

No.	*Variables*	N) LNSP		O) LNBANKR	
	Long-run exogeneity	Biblio	Economic	Biblio	Economic
33	dBubble_BE				
34	dBcycle_BE	0.1036	**0.0090***		
35	dBCTC_BE				
36	dCrisis_BE				
37	dCycle_BE	**0.0070***	**0.0055***		
38	dDepression_BE				
39	dDistress_BE	0.2992	**0.000***		
40	dEmbarrassment_BE			**0.000***	0.3647
41	dFluctuations_BE				
42	dGlut_BE	0.3329	0.2442		
43	dPanic_BE				
44	dProsperity_BE			**0.0349***	**0.0160***
45	dRecession_BE	0.9693	**0.000***		
46	dStagnation_BE				
47	dINDEXdown_BE	**0.0431***	0.1785		
48	dINDEXoverall_BE				

Significant results are in bold
* 5% benchmark is used; the H0 of the test is that the given bibliometric or economic variable is long-run exogenous in the FCVAR model.

Table 3.12: FCVAR long-run exogeneity test - two variables, category: 'Economics'. Significant results are in bold.

No.	*Variables*	N) LNSP		O) LNBANKR	
	Long-run exogeneity	Biblio	Economic	Biblio	Economic
49	dBubble_E				
50	dBcycle_E				
51	dBCTC_E				
52	dCrisis_E	0.2621	**0.0141***		
53	dCycle_E	**0.000***	**0.0039***		
54	dDepression_E				
55	dDistress_E	0.8556	**0.000***		
56	dEmbarrassment_E			**0.000***	0.8352
57	dFluctuations_E				
58	dGlut_E			**0.000***	0.3986
59	dPanic_E				
60	dProsperity_E				
61	dRecession_E	0.7149	**0.000***		
62	dStagnation_E	0.6772	**0.0294***		
63	dINDEXdown_E				
64	dINDEXoverall_E				

Significant results are in bold
* 5% benchmark is used; the H0 of the test is that the given bibliometric or economic variable is long-run exogenous in the FCVAR model.

Table 3.13: FCVAR long-run exogeneity test - five variables, category: 'Economics'. Significant results are in bold.

No.	*Variables*	H) LNRINCOME		I) UN		K) LNINVEST		L) LNPROD		M) LNCPI	
	Long-run exogeneity	Biblio	Economic	Biblio	Economic	Biblio	Economic	Biblio	Economic	Biblio	Economic
49	dBubble_E							0.3811	**0.000***	0.0875	0.0847
50	dBcycle_E	**0.0146***	**0.0261***					**0.0027***	0.2635		
51	dBCTC_E							0.0514	0.0504		
52	dCrisis_E									**0.000***	0.6244
53	dCycle_E	**0.0038***	**0.0027***					1.000	0.2873		
54	dDepression_E	0.7157	0.0929								
55	dDistress_E										
56	dEmbarrassment_E							**0.0383***	0.1638	**0.0042***	0.0613
57	dFluctuations_E										
58	dGlut_E									**0.000***	0.8357
59	dPanic_E	1.000	**0.0179***					**0.0143***	0.4549		
60	dProsperity_E									0.3249	**0.000***
61	dRecession_E							**0.0016***	**0.0439***	**0.000***	0.6603
62	dStagnation_E									**0.000***	0.7413
63	dINDEXdown_E										
64	dINDEXoverall_E										

Significant results are in bold
* 5% benchmark is used; the H0 of the test is that the given
bibliometric or economic variable is exogenous in the FCVAR model

Table 3.14: FCVAR, Portmanteau Q test of the residuals, category: ‘Business and Economics’. Significant results are in bold.

No.	H	I	K	L	M	N	O
33		0.863	0.329	0.91			
34		0.98	0.995			0.38	
35			0.974				
36	0.913	0.815			0.323		
37						0.756	
38	0.679						
39			0.056		0.453	0.621	
40					**0.017***		**0.030***
41	0.991						
42					0.645	0.857	
43							
44				**0.040***			0.343
45	0.567		0.273	0.473	0.987	0.867	
46					0.25		
47				0.241		0.268	
48		0.988		0.188			

* 5% benchmark is used.

Table 3.15: FCVAR, Portmanteau Q test of the residuals, category: 'Economics'. Significant results are in bold.

No.	H	I	K	L	M	N	O
49				0.961	0.832		
50	0.434			0.538			
51				0.371			
52					0.062	0.107	
53	0.284			0.8		0.778	
54	0.438						
55						0.074	
56				0.12	0.432		0.159
57							
58					0.909		0.693
59	0.118			0.68			
60					0.397		
61				0.757	0.986	0.874	
62					0.646	0.998	
63							
64							

* 5% benchmark is used.

Table 3.16: Diebold-Mariano test, comparing the bibliometric vs. bibliometric + economic forecasts

Literature sample	Bibliometric variables	Loss criteria MSE	Loss criteria MAE	Variables for economic forecast
BE	cINDEXdown	**0.0037***	**0.0041***	*main*
BE	cINDEXdown	**0***	**0***	*all*
BE	cINDEXoverall	**0.0168***	**0.0186***	*main*
BE	cINDEXoverall	**0.0012***	**0.0002***	*all*
E	cINDEXdown	**0.0007***	**0***	*main*
E	cINDEXdown	**0.0001***	**0***	*all*
E	cINDEXoverall	**0.0111***	**0.0041***	*main*
E	cINDEXoverall	0.0568	**0.0006***	*all*

Note: Bartlett kernel is used for the long-run variance estimation; main variables include cLNRINCOME, cUN, cLNINVEST, cLNPROD, cLNCPI; all variables include main with cLNSP and cLNBANKR. The forecast horizon is 5 lags. The H0 of the test is that the forecasts are of the same quality. All test results with only one exception suggest that the forecast using economic variables in addition to the lags of the bibliometric variables is of a better quality than the solely intrinsic forecast using only the lags of the bibliometric variables.
* 5% benchmark is used.

References for Chapter 3

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4

Spurious periodicities in cliometric series: simultaneous testing

by Vadim Kufenko

Abstract

Summary. In this paper the methodological aspects of the issue of spurious cycles are revisited: using the well-established clinometric data, I apply an empirical strategy to identify spurious periodicities and cross-validate the results. The analysis of cyclical fluctuations involves numerous challenges, including data preparation and detrending. As a result, there is a risk of statistical artifacts to arise: it is known that summation operators and filtering yield a red noise alike spectral signature, amplifying lower frequencies and thus, longer periodicity, whereas detrending using differencing yields a blue noise alike spectral signature, amplifying higher frequencies and thus, shorter periodicity. In the given paper this issue is explicitly addressed. In order to derive the stationary signals to be tested, I perform outlier adjustment, derive cycles from the series with the asymmetric band pass Christiano–Fitzgerald filter using the upper bands of the Kuznets and the Juglar cycles as cut-offs, and obtain detrended prefiltered signals by differencing the series in the absence of fractional integration. Afterwards, I simultaneously test whether the spectral densities of filtered and detrended prefiltered signals are significantly different from the spectral density of the related noise. The periodicities from the Kuznets range were not simultaneously significant, and thus are likely to be spurious; whereas ones of the Juglar and Kitchin ranges were simultaneously significant. The simultaneous significance test helps to identify spurious periodicities and the results, in general, accord with the durations of the business cycles found in other works.

Keywords: Business cycles · Spectral analysis · Spurious cycles · Fractional integration · Simultaneous testing

JEL classification: C18 · E32 · E39 · F44

4.1 Introduction

The motivation for this paper was the works on the spectral analysis of cliometric and economic time-series by Cendejas et al. (2015); Diebolt (2014); Metz (2010, 2011); Pollock (2013, 2014) and the works on the significance testing of spectral peaks by Mann and Lees (1996) and Thomson (1982). In the above-mentioned papers, the issue of spurious cycles was noted, discussed and analyzed to a certain extent. The contribution of this paper is twofold: firstly, it is shown how the spurious periodicities can arise and the exposure of spectral analysis to methods of detrending is demonstrated; secondly, an empirical strategy to conduct a simultaneous significance testing for spurious peaks in spectral densities of filtered and detrended prefiltered stationary signals based on red and blue noise confidence intervals is discussed.

The history of empirical observations on periodicity in economic variables exceeds the history of the modern business cycle theory. Whereas the works of Juglar (1862), Kondratjew (1926) and Kuznets (1930) have provided a strong impulse for theoretical and empirical works, Burns and Mitchell (1946) defined the rules of empirical identification of business cycles. In the aftermath two empirical approaches to identifying business cycles and periodicity emerged: spectral analysis of economic time series (Granger and Hatanaka, 1964) and descriptive analysis of local minimum and maximum (Bry and Boschan, 1971). Whereas certain elements of spectral and frequency analysis existed long before the emergence of the business cycle theory, the Bry–Boshan method, including the related procedures, was specifically developed to address the challenges of the National Bureau of Economic Research (NBER). These methods have some common features: they both involve detrending of the time series, application of filters or moving averages, and measuring periodicity. However, there are several fundamental differences: the Bry–Boshan procedures are traditionally applied to quarterly data and application to annual data requires calibrations[1] (see Harding, 2002); spectral analysis can be applied to a broader range of sampling rates without alterations; wheareas Bry-Boshan procedures involve descriptive identification of the turning points, spectral analysis is based on frequency decomposition of the time series. Another difference of the Bry–Boshan method is that according to Burns and Mitchell (1946, p. 3) the business cycles are not divisible into shorter cycles with amplitudes approximating their own ones, whereas spectral analysis is based on the spectral representation theorem, which states that a stochastic process is additively built up by elementary and mutually orthogonal harmonic oscillations (Cramér and Leadbetter, 1967, p. 129). Therefore, the spectral analysis allows for divisible shorter cycles, although

[1] Harding (2002, pp. 7–8) notes that adopting the Bry–Boshan procedure and identification rule to annual data may result into loss of precision. In general, quarterly data allow for a more precise identification of the turning points.

such periodicities can be either spurious (results of spectral leakage) or *hidden*, in terms of Wiener (1930, p. 128). One should note that the spurious nature of cycles does not depend on their length: long as well as short periodicities can be spurious as well.

The main task of the spectral analysis is to separate the dominant frequency from the other ones. In this paper I show that even the dominant frequency can be an outcome of spurious periodicities produced by filtering or differencing and a certain simultaneous significance test has to be applied in order to sort out spurious periodicities. The paper is organized as follows: in Section 4.2 I present a short overview of relevant literature; in Section 4.3 I focus on the methodology and data, discuss detrending issues and the testing procedure; in Section 4.4 I present spectral densities with related confidence intervals and highlight significant periodicities, including those, which remained significant after simultaneous testing; Section 4.5 includes critical assertion of the results and comparison with other known estimates of business cycle periodicities; Conclusion summarizes the findings and issues from the discussion.

4.2 Literature overview

Methodological diversity and data heterogeneity has resulted into different business cycle duration estimates with a very broad band: starting from the long waves of Kondratjew (1926) from 45–60 years; Kuznets (1930) cycles of 15-25 years; Juglar (1862) cycles of 7–11 years and to much shorter Kitchin (1923) cycles of 3–5 years[2].

One should note that the researchers, in honour of whom the cycle periodicities were named, applied different data and methods in their works. Kitchin (1923, p. 10) used the UK and the USA data on clearings, prices and interest and detrended them with a linear trend, including a structural break. Juglar (1862) used the French and the UK data on financial situations of banks and also the data on prices (see Juglar, 1862, pp. 3; 42–43 and 51). A rather descriptive analysis of the data in Juglar (1862, pp. 8 and 15) suggests that not only cycles with duration between 7 and 11 years were detected, but also shorter cycles of around 4–5 years. In Kuznets (1930), detrending with a non-linear logistic curve and smoothing with a moving average was applied on the production and price series for the USA. After detrending and smoothing, primary and secondary secular movements were discovered and the cycles cleared from such movements were analysed (see Kittredge, 1931). Afterwards, the cycles of various duration between 15 and 25 years were obtained. The longest Kondratjew (1926) cycles were derived with a similar methodology: according to Metz (2011), Kondratieff used a quadratic fit to detrend

[2] Kitchin (1923, p. 10 and 14) notes minor and major (trade) cycles of 3.5 years and around 7–8 years duration respectively.

the production series and then applied smoothing with a 9-year moving average. The periodogram analysis after replication of the original method and data, clearly indicates 37-year cycles (see Metz, 2011, p. 211); however, the Kondratieff cycles are known to reach up to 60 years. Last but not the least is the periodicity stated in Burns and Mitchell (1946, p. 3): "in duration business cycles vary from more than one year to ten or twelve years; they are not divisible into shorter cycles of similar character with amplitudes approximating their own". The latter is consistent with the Juglar cycles; or with the Kitchin cycles. The above-mentioned periodicities constitute the starting point of the discussion: which of these cycles are present in the spectrum of the long-run cliometric time series and, if they are present, can they be spurious?

The modern empirical literature on business cycles is often focused on the shorter cycles, whereas the long waves are either left out of the analysis or are not addressed in a proper manner. Considering the application of spectral analysis, interesting exceptions are: Korotayev and Tsirel (2010), Metz (2011), Cendejas et al. (2015) and Diebolt (2014). Whereas Korotayev and Tsirel (2010, p. 28) and Metz (2011, p. 229) do find mixed evidence for long waves, a clear association with the so-called Kondratieff cycles is debated, since these waves can be related to stochastic shocks and structural breaks (see Metz, 2011, p. 236). Diebolt (2014) and Cendejas et al. (2015) use the methodology which allows for long waves; however, the latter authors find evidence only for the periodicities in the Kuznets/Juglar or Kitchin ranges. The authors, who use the Bry–Boschan procedure (see Bergman et al., 1998; Christoffersen, 2000) obtain different periodicities from 19 to 6 years, or from 3 to 5 years, which corresponds to Kuznets, Juglar and Kitchin cycles.

Special attention should be paid to the notion of the spurious cycles. The general robust framework for detecting significant[3] periodicities can be found in Thomson (1982) and Mann and Lees (1996): their approach represents deriving background noise[4] from the data and testing the signal periodicities against it. The idea of spurious periodicites in economic series originates from the well-known Slutzky–Yule effect (Slutzky, 1927, 1937; Yule, 1927). Economic series are often disturbed by exogenous shocks: such superposed fluctuations and disturbances may distort spectral density and result in spurious periodicities (Yule, 1927, pp. 292-294). Coupled with this source of spuriocity, Slutzky (1937, pp. 117-121) notes that smoothing using summation operator may results into a spurious periodicity, a "summation of random causes". The implications of the Slutzky–Yule effect for detrending can be summarized as follows: applying moving averages for detrending or smoothing may lead to the emergence of cyclical preiodicities from purely

[3] The idea of a significance test for spectral density values can be traced back to the G-test from Fisher (1929).

[4] Thomson (1982, p. 1085) uses white noise, whereas Mann and Lees (1996, pp. 424–425) use red noise

random shocks. The next important milestone in this direction was the work of Nelson and Kang (1981), who proved that randomly generated series can exhibit periodicities which have no underlying reasoning and are spurious. Afterwards, at least several works explicitly addressed the issue of spurious cycles in the real economic data (e.g., Pollock, 2014; Woitek, 1997). Pollock (2013, p. 113) provides examples of spurious periodicities amplified by different detrending methods: "differencing nullifies the trend and it severely attenuates the elements of the data that are adjacent in frequency to the zero frequency of the trend ... It also amplifies the high frequency elements of the data". The summation operator, on which most statistical filtering tools are based, including moving averages, acts in an opposite way: "the squared gain of the summation operator ... gives unbounded power to the elements that have frequencies in the vicinity of zero". Therefore, filtering is likely to yield spurious periodicity for the low frequencies, whereas differencing is likely to amplify spurious periodicites at higher frequencies. Metz (2011, p. 213) notes the dilemma of comparing filtered and differenced spectral densities which we exploit in the empirical section of the paper. Woitek (1998, p. 6) also highlights the fact that statistical filters generate spurious periodicities. However, the magnitude of such spurious periodicity depends on the filtering methods: Woitek (1998, p. 12) demonstrates that the band-pass filters differ in their performance, e.g., Hodrick–Prescott (HP) filter is prone to generate spurious periodicity with higher magnitude comparing to the Baxter-King filter. Other works also highlight the distortions to the cyclical component caused by application of the HP filter (see Harvey and Jaeger, 1993).

In order to proceed to the empirical framework, we should highlight two important assumptions derived from the related literature: empirically estimated periodicities of business cycles vary, with Kondratieff cycles being the most debatable ones; detrending and filtering may generate spurious periodicites. Therefore, it is not sufficient to identify peaks in spectral densities, but rather to test whether the periodicity is likely to be spurious or not.

4.3 Methods and data

The idea is simple: if a certain frequency is significant related to the confidence interval of noise after filtering and differencing[5], then such frequency is unlikely to be spurious. However, if at least one of the these conditions is violated, the given periodicity is most likely spurious. In this section I focus on the empirical strategy and methods, and formulate the hypotheses for the simultaneous testing.

[5] In addition to differencing I apply detrending with a linear trend, refraining from any nonlinear interference, which can potentially generate spurious periodicities, similar to the ones expected to be found after filtering.

In order to begin, I eliminate the time series outliers with the help of auto regressive moving average (further ARIMA), as in Metz (2010, p. 57). Three different types of outliers are accounted for: additive outliers (AO), level shifts (LS) and temporary changes (TC). This allows us to clear the original data from potential distortions driven by structural breaks. The outlier adjustment is performed with the functions from de Lacalle (2015) and the pin-pointing of the events related to outliers (see Table 4.9) is based on Darné and Diebolt (2004)[6]. Afterwards, I perform filtering with the asymmetric Christiano–Fitzgerald (further CF) filter (see Christiano and Fitzgerald, 2003) based on the functions from Balcilar (2007). The choice of given filter is justified because of the advantages of the changing gain function – namely the asymmetric feature – comparing to the Baxter-King filter[7] (see Metz, 2011, p. 215). I expect that the filter will dampen high frequencies, amplify the low frequencies and generate spurious periodicities. Thus, I will need a reference for comparing the findings: the differenced data, to which I will refer as detrended and prefiltered[8]. As noted previously, differencing may affect the spectral density is a reverse way: it will amplify the high frequencies and dampen the low ones, thus the risk of spurious periodicities still exists (see Pollock, 2013; Salas, 1980, pp. 293 and 113 respectively). I verify the stationarity of the filtered and differenced data with the Kwiatkowski et al. (1992) test[9] (further, KPSS) using the functions from Trapletti and Hornik (2015).

Whereas for the asymmetric CF filter I use the upper bounds of the Kuznets and the Juglar cycles (25 and 11 years respectively[10]), before applying first differences one needs to check whether fractional integration exists – if so, the signals would be 'overdifferenced'. If that is the case, then the differenced data would not be the best benchmark because the long range dependence (if any are present) would be corrupted by differencing and fractional differencing should be applied. In case if the fractional difference parameter d is in a proximity of one, the first degree of differencing is justified. After the adjustment for outliers, I estimate the

[6] Additional sources for the outlier information are taken from Abildgren et al. (2011); Butlin (1963); Campbell (2012); Chisholm (1963); Coghlan (2011); Haeger et al. (2011); Herrick (1908); Hickson and Turner (2002); Neal (1998); Shaw (1984)

[7] The original version of the Baxter–King filter (see Baxter and King, 1995, 1999) can be compared to the symmetric CF filter with a specified gain function. One should note that comparing to the well-established Hodrick–Prescott filter (see Hodrick and Prescott, 1981), the simple Baxter–King filter with a specified gain function is less prone to yielding spurious periodicities for annual data as noted in Woitek (1998, Figure 3 on p. 12). There have also been attemptes to introduce an asymmetric extension of the Baxter-King filter (see Buss, 2011).

[8] This data will not be filtered, but only differenced once and detrended with a linear trend exactly as in Woitek (1997, p. 88, footnote 20).

[9] The H_0 of the KPSS test is that the series are stationary.

[10] This explicitly allows the existence of such periodicities in the series, even if they will turn out to be spurious.

parameter d with the help of two methods: the unit root log periodogram regression as in Phillips (1999, 2007) and the multivariate log periodogram regression as in Robinson (1995). For these purposes the functions from Baum and Wiggins (2000b) and Baum and Wiggins (2000a) were used. Phillips (2007) notes that the standard Geweke-Porter-Hudak estimator of d from Geweke and Porter-Hudak (1983) may be biased for cases $0.5 < d < 1$. Kim and Phillips (2006) show that the log periodogram regression is consistent for such cases when $0.5 < d < 1$ including cases when $d=1$ (see Hurvich and Ray, 1995). Therefore, the Phillips (2007) test[11] based on the unit root log periodogram regression is an ideal tool to check whether the data was differenced correctly. Robinson (1995) multivariate test[12] will answer the question whether the same degree of differencing should be applied to all series. The latter test is applied merely as a cross-validation tool for the Phillips test.

Comparing two spectral densities of the filtered and detrended prefiltered signals is not sufficient and a reference benchmark spectral density with confidence intervals for blue or red noise[13] will be introduced. The derivation of these types of noise from the signals will be based on the functions from Bunn et al. (2015) and Schulz and Mudelsee (2002). In addition, for generation of red and blue noise, I have applied certain functions from Borchers (2015) and Zeileis and Grothendieck (2005): for certain countries the autocorrelation parameter was positive whereas for the other countries is was negative. One has to note that Granger (1966) and Levy and Dezhbakhsh (2003)[14] found that most macroeconomic variables follow the spectral density comparable to the red noise; however, there are also other findings: e.g. Bjørnland (2000, pp. 379–380) demonstrated other spectral patterns in the filtered GDP data. Indeed, in case of negative autocorrelation coefficient estimated for the stationary signal, higher frequencies would be stronger yielding a blue noise comparable spectral density; whereas if the coefficient is positive, the spectral density will resemble red noise with emphasis on lower frequencies[15]. Therefore, the appropriate confidence intervals based on the red or blue noise derived from each country's signals would be helpful to test the significance of the

[11] The H_0 for the Phillips (2007) test is that $d=1$, implying that the series contain a unit root and have to be differenced once. If the H_0 is not rejected, the series are most likely not fractionally integrated. Rejection would mean fractionally integrated series and the need to apply fractional differencing instead of first differencing.

[12] The H_0 for the Robinson (1995) test is that d coefficients are the same for all series.

[13] For theoretical details see Mann and Lees (1996). In the paper a similar test is conducted; however, simultaneously for both types of signals.

[14] Levy and Dezhbakhsh (2003) report various spectral shapes depending on the economic characteristics of the countries: the spectral patterns for developing countries are wider and are saturated around mid-range frequencies, whereas the developed countries exhibit red noise comparable pattern with peaks at lower frequencies.

[15] For a detailed discussion on the relation between the spectral density and the autoregressive coefficients, see Jenkins and Watts (1968, pp. 264–275).

peaks of the spectral density function. Thus it will be possible to identify spurious cycles which appear only after application of the CF filter or differencing and those periodicities, which are significant relative to the spectral density of the related noise for both types of signals, and thus are unlikely to be spurious. The tests are conducted for three levels of confidence intervals: 90, 95 and 99%; however, the 90% level is set as the lowest threshold for significance[16] for both types of signals. For a given frequency value, the null hypothesis in this case would be that the power of the spectral density of the signal is not significantly different from the confidence interval of the power of the spectral density of the red or blue noise, derived from this signal (by analogy with Bunn et al., 2015; Schulz and Mudelsee, 2002). Therefore, two nulls for the simultaneous testing are formulated:

$$H_{0,i}^{filtered} : S_i^{filtered} \leq S_i^{filt\,noise} \tag{4.1}$$

$$H_{0,i}^{prefiltered} : S_i^{prefiltered} \leq S_i^{pref\,noise} \tag{4.2}$$

where $S_{filtered}$ and $S_{prefiltered}$ are the powers of the spectral density of filtered and detrended prefiltered signals; i is a frequency index; and $S_{filt\,noise}$ and $S_{pref\,noise}$ are the confidence intervals of the powers of the red or blue noise derived from the related signals.

The important feature of the testing strategy is to conduct the same significance test on the filtered and detrended prefiltered data to exclude the periodicities which are obviously spurious. If the null is rejected for a given frequency, but only for one type of a signal, it is likely to be spurious.

The spectral density of the signals is estimated with the general-purpose Blackman–Harris window based on Harris (1978) which can perform very well in suppressing the side lobes thus minimizing spectral leakage (see Prabhu, 2013, p. 306). For a fine resolution 7 segments with 50% overlapping are set. However, since the main lobe would be wide it may complicate the exact comparison of the spectral densities of the filtered and differenced data. Therefore, in case of minor discrepancies between the two densities, the nearest neighbouring frequency within the 0.15 year range will be taken into account. In the tables such cases will be marked accordingly with a circle.

[16] Although the conventional level of confidence intervals is usually 95%, the 90% benchmark is set and the significance considering this confidence interval is denoted with *, since higher levels could be too restrictive for economic data, which is subject to numerous exogenous shocks. Therefore, if the power of the signal at the given frequency is significant considering the 90% confidence interval one can reject the null hypothesis that the power of this frequency is not significantly different from the power of the spectral density function of red or blue noise.

Finally, in the discussion I revisit the results and compare them to the findings of other researchers. In addition, the methods applied will be critically asserted and the related issues will be noted.

The dataset is taken from Bolt and van Zanden (2013): it is a well-established dataset and the results obtained using these series can be compared with the results of other researchers who also used it, bearing in mind methodological differences. By design, the gain function of the statistical filters as well as the methods of the spectral analysis are exposed to the sample size. Thus the major goal during the selection of an appropriate dataset was to select the longest consistent series available. The countries were selected according to two major criteria: no need to interpolate any observations starting from 1820 to 2010 and no need to divert from one single framework of outlier detection and filtering. There were six countries which fit this criterion: Australia, Denmark, the Netherlands, Sweden, the UK, the USA. The same dataset was used in Cendejas et al. (2015) and Diebolt (2014), however starting from 1870, whereas in this paper I use the times frames from 1820 to 2010 with 191 annual observations.

4.4 Results

I start with adjusting the series to AO, LS and TC. As it follows from Fig. 4.4 adjusting is crucial: for Australia 10 outliers were detected; for Denmark seven were detected; for the Netherlands five; for Sweden five; for the UK four and for the USA nine. The adjusted data is not stationary and all of the series contain a unit root according to the KPSS test and have to be transformed. The KPSS test results of the adjusted data itself contain little useful information other than the fact that the series are not stationary. Further transformation is needed. This transformation is twofold and I obtain two types of stationary signals: I filter the series with the asymmetric CF filter and apply first differences. In question are the parameters of filtering and differencing: the CF filter is a band-pass filter, where the cut-off frequency is crucial; while for differencing the degree is important. Whereas I decide to set the filter cut-off periodicity to 11 (Juglar cycles) and 25 (Kuznets cycles) as per the goal to test spurious periodicities, the degree of differencing has to be tested. Thus, I first test the presence of fractional integration and whether using first differences is appropriate.

In Table 4.1 the Phillips (2007) and Robinson (1995) test results are reported. These point out two facts: the estimated fractional difference parameter $\hat{d}$ for all countries is in the proximity of one, except only one case for the power of 0.5 which corresponds to only 13 harmonic ordinates for the USA data, which is too few; for all other powers the null that d=1 is not rejected. Robinson (1995) test validates the null of the equality of $\hat{d}$ for all six cases, which is also close to one. Therefore, using first differences is justified. In Tables 4.3, 4.2 and 4.4 I check whether the filtered and differenced series are stationary: all pass the test.

The fluctuations obtained with the CF filter and differencing exhibit distinct features resembling those, named in Section 4.2: the filtered cycles with the cut-off periodicity of 25 years from Figure 4.5 are less dense than the filtered cycles with a cut-off of 11 years from Fig. 4.6. Most dense are the fluctuations obtained by first differencing: the detrended prefiltered data from Fig. 4.7. Recalling that filtering dampens high frequencies and amplifies lower ones (whereas differencing acts the other way around) the figures exhibit exactly these features and I anticipate discrepancies in spectral patterns. The risk of emergence of spurious periodicities generated by the filter is obvious. Considering the autoregressive coefficients for generation of noise (see Table 4.5), it is obvious, that filtering amplifies lower frequencies, since the coefficients are positive for the filtered fluctuations; whereas for the detrended prefitlered, the coefficients are negative, with one exception to the UK. It is important to note that most of the coefficients are remote from zero, except for the filtered fluctuations for Australia. Therefore, an appropriate modeling of the noise process for each case is preferable rather than setting a white noise benchmark for all cases.

Let us proceed to the spectral analysis and simultaneous significance testing. Figures 4.1, 4.2 and 4.3 display confidence intervals and frequency (periodicity) peaks after applying the Blackman–Harris window. The exact values of significant periodicities are given in Tables 4.6, 4.7 and 4.8. The filtered cycles of Australian data demonstrate that the CF filter functions well and eliminates all periodicities below the cut-off: the first significant periodicity of the CF filtered cycles with the cut-off at 25 years, resembling the Kuznets cycles, is at 17.455; the cycles with the cut-off at 11 years, similar to the Juglar cycles, show a significant peak at 8.348. After examination of the spectrum of the detrended prefiltered data it becomes obvious that the peak of 17.455 is just a leakage from the zero frequency and the second peak is present; however, not significant at any levels. The differenced data are compared to the blue noise, with higher frequencies prevailing. The periodicities, which are significant for the filtered and detrended prefiltered fluctuations, are: 4.085; 2.743 and 2.110 for Australia. For Denmark the situation is similar: the Kuznets cycle peak is at 19.2 years – this frequency can not be confirmed for the detrended prefiltered series; the Juglar cycle peak is simply a leakage from the lower frequency peak and it is not significantly different from the red noise spectrum. The frequencies which are significant for both filtered and detrended prefiltered series are: 5.189 (5.05) and 3.2 years. For the Netherlands the Kuznets and Juglar cycle periodicities (21.33 and 10.11) are significant but are not confirmed by the spectrum of the differenced data. Yet the periodicity of 9.6 turned out to be significant across two signals: the Juglar and for the detrended prefiltered cycles. For Sweden the situation is similar, but the periodicity of 5.053

(4.923) appears to be simultaneously significant for both filtered and differenced fluctuations. For the UK the Kuznets periodicity of 14.769 is significant (and can be distinguished in the differenced data, although for the differenced signal it is not significant) and the Juglar peak is at 8.348 - the latter turns to be simultaneously significant, although it may partly capture the leakage from lower frequencies. An intriguing picture is displayed for the USA: both, the Kuznets peak at 24 years and Juglar peak at 9.143 are significant for the filtered series and can be observed in the prefiltered detrended data. They are not simultaneously significant, but can be distinguished. For the USA, the simultaneously significant periodicities are only at 4.085 and 2.133 years.

Since, bearing the test results in mind, the series are not fractionally integrated and the first degree of differencing is appropriate, one could argue that the spectral density of differenced data, to which I refer as "detrended prefiltered", is a valid benchmark to eliminate spurious cycles resulting from filters in general, and the asymmetric CF in particular. Although several low frequencies, e.g., 14.769 for the UK, 16 for Sweden, 17.455 for Australia, 19.2 for Denmark and the Netherlands and 24 years for the USA were significantly different from the red noise confidence intervals for the filtered data; they were not validated by the detrended prefiltered data. The latter periodicities could be attributed to the Kuznets range and, referring to Hypotheses 4.1 and 4.2, for these values the nulls are not simultaneously rejected. A similar case is observed for the Juglar periodicities: 8.348 for Australia; 9.143 for the Netherlands; 8.348 for Sweden and 9.143 for the USA. The only exceptions are the Netherlands with 9.6 and the UK signals, where 8.348 year periodicity was simultaneously significant: here rejection of Hypotheses 4.1 and 4.2 is observed for the Juglar and detrended prefiltered cycles. Concerning the latter case, one should note that this periodicity for the differenced data was significant relative to noise only at the 90% level not even reaching the 95% confidence interval. Therefore, one can only state that the evidence, that the Juglar-like periodicity is not likely to be spurious, is weak. On the contrary, higher frequencies and shorter periodicities are robust: 2.11, 2.743 and 4.085 for Australia; 5.189 (5.053) and 3.2 for Denmark and 4.085 and 2.133 for the USA are simultaneously significant: for these periodicities, Hypotheses 4.1 and 4.2 are simultaneously rejected. Therefore, there is strong evidence that the so-called Kitchin periodicities may not be spurious and manifest themselves in filtered and differenced data.

Table 4.1: Tests on fractional integration, $\hat{d}$ coefficients and their equality

Phillips (2007) Modified Log Periodogram Regression estimator, H_0: d=1												
	lnAUSTRALIA_adj		lnDENMARK_adj		lnNETHERLANDS_adj		lnSWEDEN_adj		lnUK_adj		lnUSA_adj	
Power	$\hat{d}$	P>z	$\hat{d}$	P>z	$\hat{d}$	P>z	$\hat{d}$	P>z	$\hat{d}$	P>z	$\hat{d}$	P>z
0.50	1.131	0.461	1.031	0.859	1.007	0.969	1.167	0.347	1.167	0.346	0.934	0.711
0.55	1.141	0.364	1.039	0.800	1.085	0.586	1.075	0.628	0.912	0.571	0.916	0.589
0.60	1.119	0.375	0.991	0.949	0.959	0.760	1.134	0.315	0.847	0.252	0.831	0.206
0.65	1.112	0.341	0.999	0.994	0.999	0.992	1.093	0.427	0.816	0.117	0.962	0.747
0.70	1.097	0.345	0.915	0.405	0.922	0.448	1.002	0.987	0.919	0.429	1.002	0.984
Robinson (1995) test for equality of $\hat{d}$ coefficients, H_0: $\hat{d}$ coefficients are the same for all six series												
F(5,666) = 0.2834 and P>F = 0.9223												

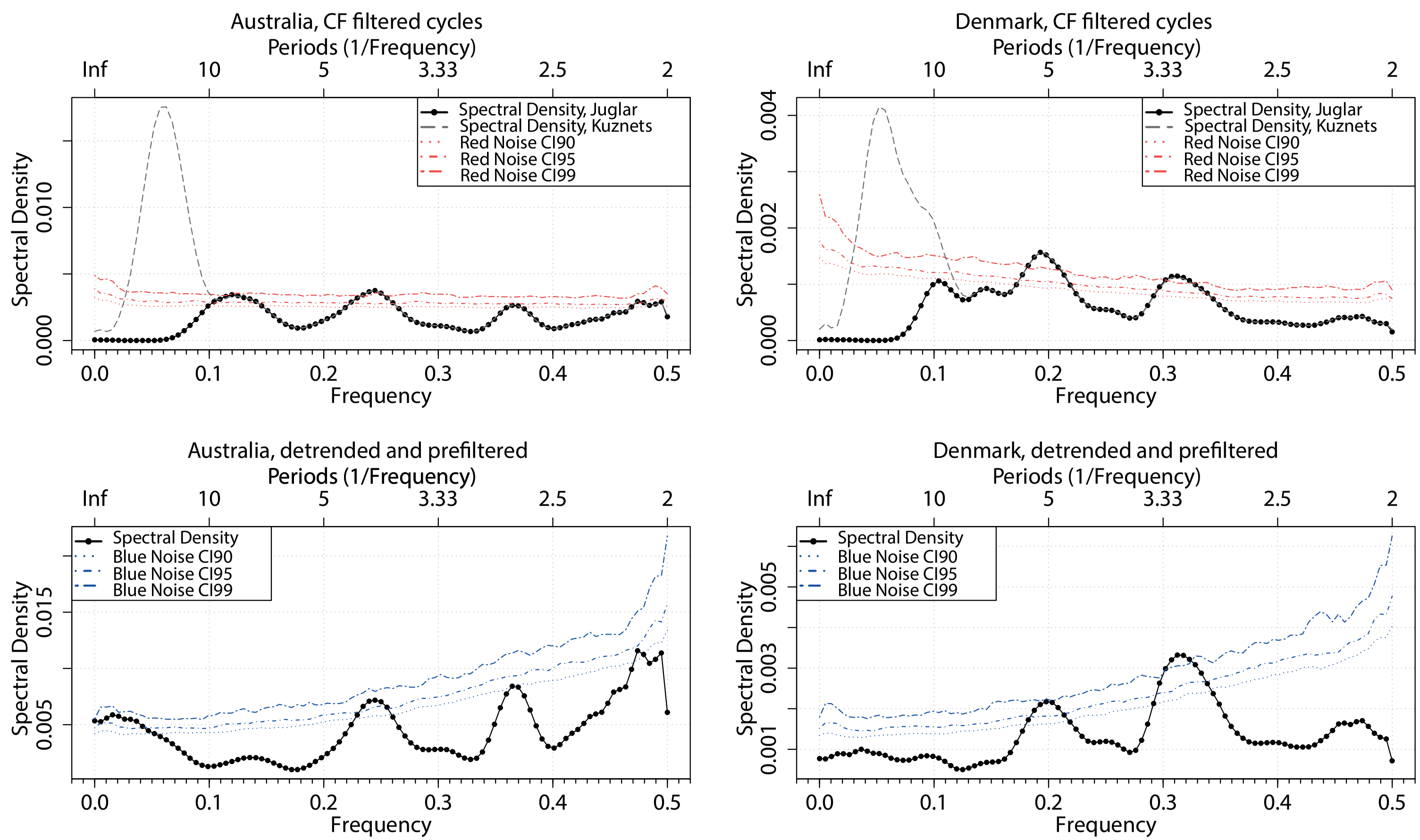
Table 4.2: Stationarity test of the filtered Kuznets cycles

CF filtered, Kuznets KPSS Test for Level Stationarity		
	Test statistic	P value
Australia	0.0139	> 0.1
Denmark	0.0183	> 0.1
The Netherlands	0.0136	> 0.1
Sweden	0.0135	> 0.1
UK	0.0121	> 0.1
USA	0.0164	> 0.1

Table 4.3: Stationarity test of the filtered Juglar cycles

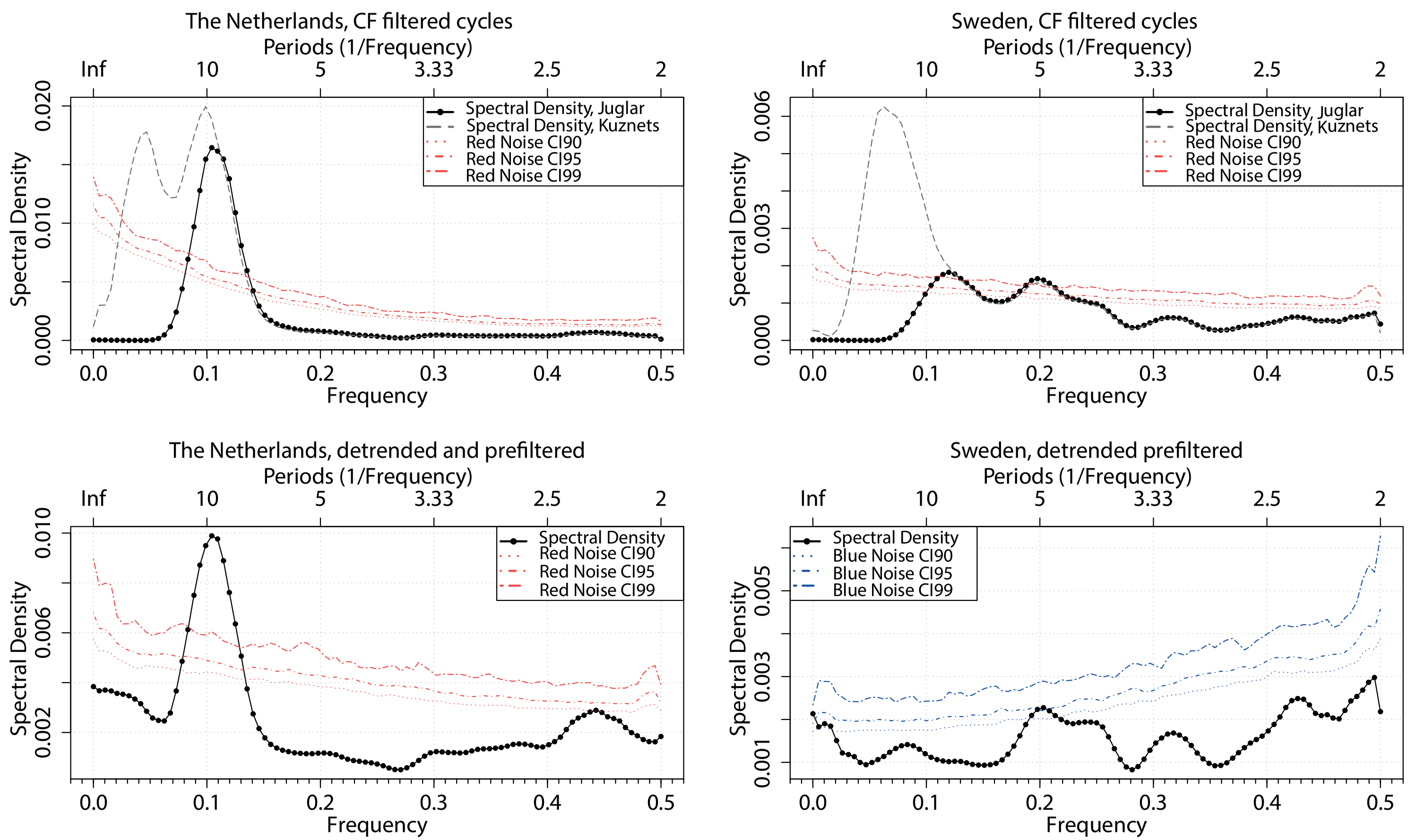
CF filtered, Juglar KPSS Test for Level Stationarity		
	Test statistic	P value
Australia	0.0089	> 0.1
Denmark	0.0076	> 0.1
The Netherlands	0.0058	> 0.1
Sweden	0.0076	> 0.1
UK	0.0065	> 0.1
USA	0.0065	> 0.1

Fig. 4.1: Australia and Denmark: filtered and prefiltered spectral densities



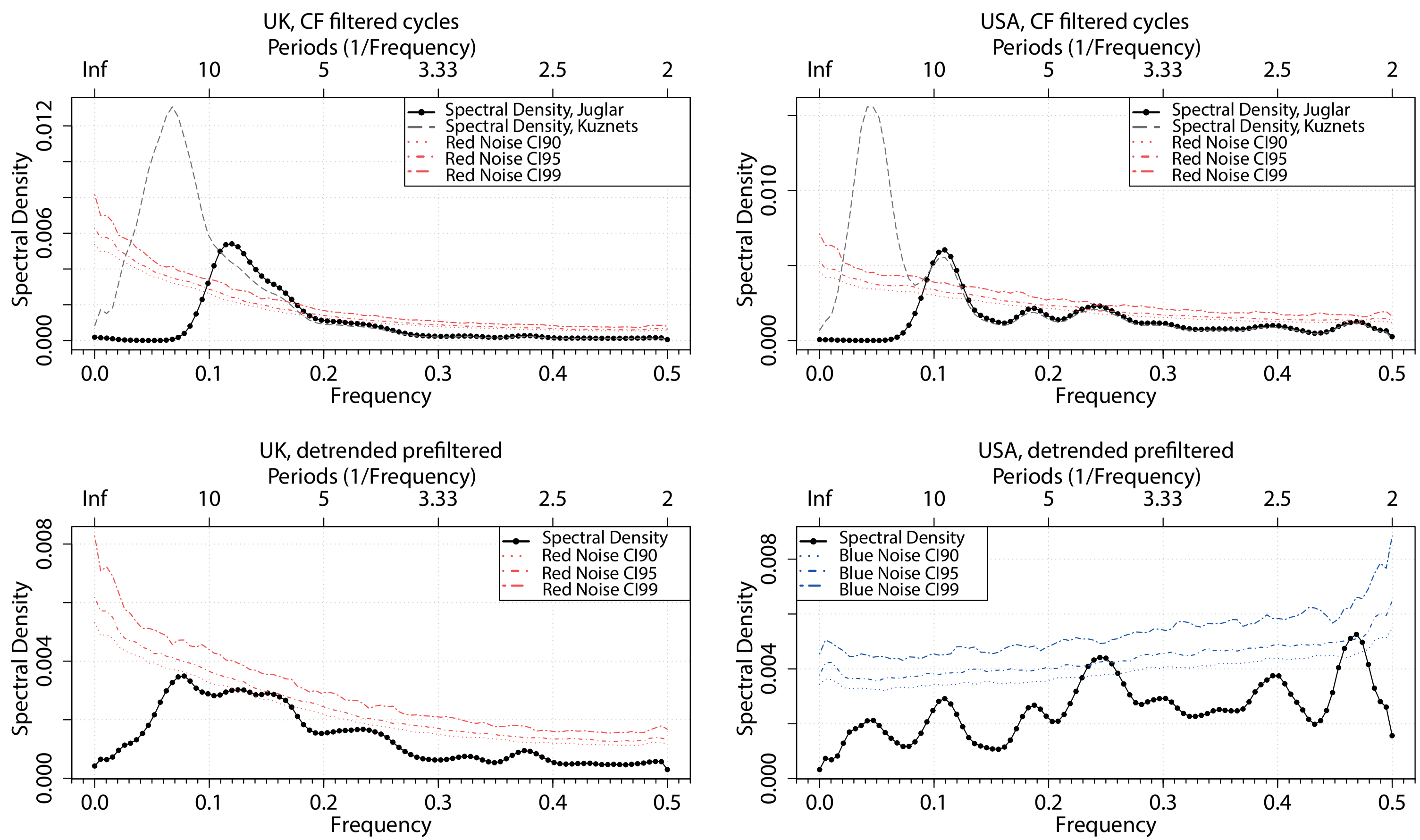
Details: Blackman-Harris window applied with 7 segments and 50% overlapping.

Fig. 4.2: The Netherlands and Sweden: filtered and prefiltered spectral densities



Details: Blackman-Harris window applied with 7 segments and 50% overlapping.

Fig. 4.3: UK and USA: filtered and prefiltered spectral densities



Details: Blackman-Harris window applied with 7 segments and 50% overlapping.

Table 4.4: Stationarity test of the detrended prefiltered series

Detrended and prefiltered	KPSS Test for Level Stationarity	
	Test statistic	P value
Australia	0.2151	> 0.1
Denmark	0.1523	> 0.1
The Netherlands	0.0376	> 0.1
Sweden	0.1995	> 0.1
UK	0.3279	> 0.1
USA	0.1974	> 0.1

Table 4.5: Estimated coefficients for generation of noise

	AR(1) coefficient		
	CF (25)†	CF (11)	Prefiltered
Australia	0.488	0.0153	-0.236
Denmark	0.526	0.148	-0.229
The Netherlands	0.662	0.243	0.128
Sweden	0.476	0.125	-0.145
UK	0.76	0.499	0.329
USA	0.673	0.281	-0.0815

† for presentation purposes only the background noise for CF (11) and detrended prefiltered signals is displayed on the figures

Table 4.6: Significant periodicities of CF filtered cycles in years, Kuznets cycles

Frequency peak	Australia	Denmark	The Netherlands	Sweden	UK	USA
1st	17.455	19.2	21.33	16	14.769	24
2nd	8.348	5.189 ○	10.11	5.053 ○	-	9.143
3rd	4.085 *	3.2 *	-	-	-	4.085 *
4th	2.743 *	-	-	-	-	2.133 *
5th	2.110 *	-	-	-	-	-

* denotes simultaneous significance of the peak value at least at the 90% level

○ denotes simultaneous significance of a nearest neighbour peak value (within 0.15 years) at the 90% level

Table 4.7: Significant periodicities of CF filtered cycles in years, Juglar cycles

Frequency peak	Australia	Denmark	The Netherlands	Sweden	UK	USA
1st	8.348	5.189 ∘	9.6 ∗	8.348	8.348 ∗	9.143
2nd	4.085 ∗	3.2 ∗	-	5.053 ∘	-	4.085 ∗
3rd	2.743 ∗	-	-	-	-	2.133 ∗
4th	2.110 ∗	-	-	-	-	-

* denotes simultaneous significance of the peak value at least at the 90% level
∘ denotes simultaneous significance of a nearest neighbour peak value (within 0.15 years) at the 90% level

Table 4.8: Significant periodicities of detrended and prefiltered cycles

Frequency peak	Australia	Denmark	The Netherlands	Sweden	UK	USA
1st	4.085 ∗	5.053 ∘	9.6 ∗	4.923 ∘	8.348 ∗	4.085 ∗
2nd	2.743 ∗	3.2 ∗	2.26	-	6.621	2.133 ∗
3rd	2.110 ∗	-	-	-	-	-

* denotes simultaneous significance of the peak value at least at the 90% level
∘ denotes simultaneous significance of a nearest neighbour peak value (within 0.15 years) at the 90% level

4.5 Discussion

The discussion covers certain features of the testing strategy and other methodological or data related issues. I start with comparing the simultaneously significant periodicities with the findings present in other papers and then focus on the possible reasons for similarities and discrepancies.

Woitek (1997, p. 92) also compares filtered and differenced estimates, however without significance testing: for the GDP series of the OECD countries he finds that the cycle duration for the fluctuations obtained with the Hodrick–Prescott filter is around 8.14 years and for the differenced data – around 7.13. In Section 4.3 it was noted, that the given filter is more vulnerable to generation of spurious periodicities than other band-pass filters: in Woitek (1997, pp. 134–142) the issue of spurious periodicities is explicitly discussed. Bergman et al. (1998, p. 74) show cycle durations from 3.8 to 4.6 for Denmark; from 3.4 to 5.5 for the Netherlands; from 4.7 to 5 for Sweden; from 3.5 to 6 for the UK and from 4.1 to 6.3 for the USA using the detection methodology similar to Bry-Boschan coupled with the Baxter-King filter, which, as previously noted, is less prone to generating spurious periodicities; however, it is symmetric and thus, may be inferior to the asymmetric CF filter for the frequencies below the cut-off. Nevertheless, the findings for Sweden, Denmark and the USA are in the proximity of the above-mentioned values. Cashin and Ouliaris (2001, p. 16) reports lengths for Autralian business cycles using the Bry-Boschan methodology: the values range from 3.2 to 6.1. This range resembles the simultaneously significant findings: 2.743 and 4.085. Cendejas et al. (2015, pp. 22–25) find durations of 6.9 for Australia; 5.3 for Denmark; 3.9 for the Netherlands; 4.5 for Sweden; 3 for the UK and 5.2 for the USA. One has to note that for Sweden and the UK the estimation was slightly altered. These findings also resemble simultaneously significant periodicities in this paper with an exception of the UK. Regarding the UK, Metz (2011, p. 235) finds irregular cycles with a length of around 11 years which is closer to my estimate of 8.348 than the findings of other researchers. In addition, Mills (2007, p. 222), reports cycles of 8.2 years for the UK real interest rates - although, real interest rates are a different variable, it can be used as a proxy for real economic activity. Finally, Diebolt (2014); Diebolt and Guiraud (2000) report longer periodicities, corresponding to Juglar and Kuznets cycles from 7 to 22 years: I detect manifestations of these long cycles in all countries; however, most of them did not turn out to be simultaneously significant with an exception of 8.348 for the UK and 9.6 for the Netherlands.

Let us revisit the testing strategy and potential caveats. The adjustment of the series to outliers is related to many risks, e.g., spurious outliers or shifts and thus incorrect adjustment (see the example of such discussion in Metz, 2010, pp. 58-62). This issue is related to the empirical strategy of this paper, since I had to apply the same outlier detection methodology, namely the ARIMA models, for the adjustment. Applying different methods for each unique situation would be more appropriate; however in that case, heterogeneity in methodology would increase the exposure of the spectral densities to purely technical features and comparing them would be questionable. The second issue is related to testing: the non-rejection of the null hypothesis as in (4.1) and (4.2) has clear implications: the given periodicity is most likely spurious. The implications of rejection of both nulls are more complex. Even if a certain frequency is significant in both cases, there is still a risk of this periodicity to be spurious. This risk comes from two sources: the benchmark spectral density of the noise and the spectral density of the signal itself. For simplicity, I assume that the noise is an autoregressive process of the first order, or AR(1), which is sufficient for the purposes of this paper. One should note that models for the background noise of a higher order, e.g. AR(2), may introduce spurious oscillations due to their design (see Mann and Lees, 1996, pp. 411-412), therefore AR(1) is preferable. The second issue is related to the fact that two cases of amplification are compared: amplified lower frequencies and amplified higher ones. Although the degree of differencing is justified by the test on fractional integration and the asymmetric CF filter is a well-established tool, surpassing the symmetric Hodrick–Prescott and Baxter–King filters in certain aspects[17]; the rejection of the nulls should not be seen as an identification of the true dominant periodicity, but rather an attempt to sort out the ones, likely to be spurious.

An important point to discuss is whether one could resort to wavelets in order to identify spurious periodicities. Indeed, using wavelets, one could estimate the trend (see Gilbert, 1999), remove it by the means of a wavelet-based filter and analyse the deviations. However, the wavelet transform would yield the corresponding spectral density without any distortions only if the choice of the wavelet function was appropriate (see Tabaru and Shin, 2003). Spectral analysis is exposed to a similar risk. Therefore, in case of wavelets the risk of emergence of spurious periodicities during the transformation is not completely eliminated. Another issue with the

[17] One has to note, that there are more sophisticated wavelet alternatives, filters with optimal cut-off frequency estimation and extensions to the exiting filters (see Baubeau and Cazelles, 2008; Buss, 2011; Iacobucci and Noullez, 2005; Çağrı Akkoyun et al., 2012); in order to answer the given research questions, I deliberately used the upper bounds of the Kuznets and Juglar cycles in order to capture any distinct periodicities in that range and perform simultaneous significance testing. I should also note that despite the superior performance of the asymmetric CF filter, according to Iacobucci and Noullez (2005, pp. 95–96) the CF filter is only nearly optimal and is also prone to generating spurious cycles: the gain function with asymmetric weights allows to assign flexible weights to different frequencies, which successfully dampens frequencies below the cut-off (observed on Fig. 4.5 and 4.6), but this very feature can induce phase shifts. Even though, that the filtered cycles pass the KPSS test, such anomalies can not be completely ruled out. Nevertheless, for the purposes of this paper, the asymmetric CF filter performs well and eliminates frequencies below the selected cut-off points. This leaves the Kondratjew range out; however, as noted in Section 4.2, such periodicities are the most debatable ones.

application of wavelets, would be the simultaneous testing. It would involve a large number of transformed signals, the approximations of their densities and the densities of their noise. Bearing similar risk of emergence of spurious results, there will be other uncertainties related to the testing.

Finally, one has to stress the importance of the choice of the detrending methods for the broad implications of business cycle research. While Harvey and Jaeger (1993) stress the distortions of the cyclical component related to filtering, Canova (1998) highlights the impact of the choice of detrending methods on the stylised facts, derived from the analysis, e.g., the impulse-response simulations and strength of correlation between detrended fluctuations of different variables (hours and real wage, or productivity and output).

4.6 Conclusion

The debates on the periodicity of economic fluctuations involve more than 150 years of fruitful theoretical and empirical research. The problem of spurious periodicities has been accompanying these debates, especially during the period of emergence and evolution of statistical methods of analysis. The well-established periodicities of economic fluctuations are ranged from the long waves of Kondratjew (1926) of 45–60 years; Kuznets (1930) cycles of 15-25 years; Juglar (1862) cycles of 7–11 years and much shorter Kitchin (1923) cycles of 3–5 years. Various data adjustment, filtering and detrending techniques are prone to generating spurious periodicities: filtering based on summation operators may amplify low frequencies and dampen the higher ones; whereas differencing amplifies high frequencies and suppresses the lower ones. In this context, the main research question of this paper can be formulated as follows: which of these cycles are present in the spectrum of the long-run cliometric time series and, if they are present can they be spurious?

In order to address this question, the cliometric data for Australia, Denmark, the Netherlands, Sweden, the UK and the USA during 1820-2010 were used and the following empirical strategy have been applied: I adjusted the series for additive outliers, level shifts and temporary changes; tested on fractional integration; obtained two types of cyclical fluctuations: with the asymmetric Christiano–Fitzgerald filter (filtered series) and using first differences (detrended prefiltered); derived blue and red noise confidence intervals; estimated spectral densities using the Blackman-Harris window and conducted simultaneous testing of the significance of the spectral densities of the filtered and detrended prefiltered series. Those preiodicities which were not simultaneously significant for the filtered and detrended prefiltered series are most likely spurious.

The tests suggest absence of fractional integration and thus first degree of differencing is appropriate. The filtered series allow for Kuznets and Juglar cycles up to 25 and 11 years respectively. After conducting simultaneous significance tests at 90, 95 and 99% levels, I find that even the most distinct peaks at lower frequencies (longer periodicities) are not significantly different from the confidence intervals of the related noise for the detrended prefiltered data. Thus, periodicities from 16 to 24 years, which were significant for the filtered series (as in Diebolt, 2014; Diebolt and Guiraud, 2000), were not simultaneously significant for the detrended prefiltered ones. The longest periodicities, which were simultaneously significant relative to noise at least at the 90% confidence interval was 9.6 for the Netherlands and 8.348 for the UK; other simultaneously significant periodicities are ranged from 2.11 to 5.189 which is close to findings of Bergman et al. (1998); Cashin and Ouliaris (2001); Cendejas et al. (2015); Woitek (1997).

Even though that the Kuznets cycles manifest themselves, it is possible to find simultaneously significant evidence only for the Juglar and Kitchin cycle lenghts. Simultaneous testing of the significance of spectral densities of the given series against the noise confidence intervals helps to identify periodicities, which are most likely spurious; however, the exact identification of the true dominant frequency is still an open question. The simultaneous non-rejection of the nulls is straightforward and implies that the given peak is not significantly different from the spectral pattern of the related blue or red noise; whereas the rejection case may still be prone to issues mentioned in the discussion.

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4.8 Appendix

Table 4.9: Detailed outlier information

Country	Year	Type	Coef.	T-stat.	Event
Australia	1830	LS	0.162	4.029	End of drought of 1829
	1835	TC	0.148	3.943	Series of droughts
	1839	AO	-0.117	-3.484	Severe draught
	1842	TC	-0.226	-5.864	Financial crises (1841-1843)
	1850	AO	-0.142	-4.250	Severe drought
	1853	AO	0.139	4.139	End of South Australian devaluation of 1852
	1858	AO	-0.216	-6.451	Drought of 1857
	1892	LS	-0.178	-4.371	Banking crisis of 1890s
	1930	LS	-0.188	-4.581	Great Depression
	1942	TC	0.148	3.900	WWII
Denmark	1855	AO	0.078	3.884	Recession and Monetary crisis of 1855-1858
	1917	TC	-0.099	-4.310	WWI
	1918	AO	-0.078	-3.742	WWI
	1940	LS	-0.172	-6.998	WWII
	1941	TC	-0.155	-6.551	WWII
	1945	AO	-0.104	-5.155	WWII
	2009	LS	-0.089	-3.681	Global financial crisis
The Netherlands	1830	TC	-0.113	-4.277	The Belgian Revolution
	1917	AO	-0.102	-4.60	WWI
	1918	AO	-0.19	-8.61	WWI
	1944	TC	-0.488	-18.17	WWII
	1945	AO	-0.263	-13.491	WWII
Sweden	1868	TC	-0.103	-3.943	Severe famine of 1866-1868
	1870	LS	0.104	3.680	End of famine
	1918	LS	-0.139	-5.098	WWI
	1932	TC	-0.094	-3.776	Great Depression
	1946	LS	0.094	3.469	End of WWII
UK	1826	AO	-0.067	-4.420	Financial crisis of 1825-1826
	1850	TC	-0.173	-8.297	Commercial/financial crisis of 1847-1848
	1919	LS	-0.102	-4.095	End of WWII
	1926	AO	-0.060	-3.977	General Strike
USA	1908	AO	-0.095	-3.421	Financial crisis of late 1907
	1914	TC	-0.114	-3.575	WWI
	1931	TC	-0.125	-3.764	Great Depression
	1932	TC	-0.186	-5.715	Great Depression
	1933	TC	-0.122	-3.710	Great Depression
	1941	TC	0.117	3.553	WWII
	1942	TC	0.184	4.920	WWII
	1943	TC	0.166	4.657	WWII
	1946	LS	-0.263	-7.097	End of WWII

Sources: Darné and Diebolt (2004) and Chisholm (1963); Shaw (1984)
Abildgren et al. (2011); Butlin (1963); Hickson and Turner (2002); Neal (1998)
Campbell (2012); Coghlan (2011); Haeger et al. (2011); Herrick (1908)

Fig. 4.4: Series, adjusted for outliers using ARIMA models

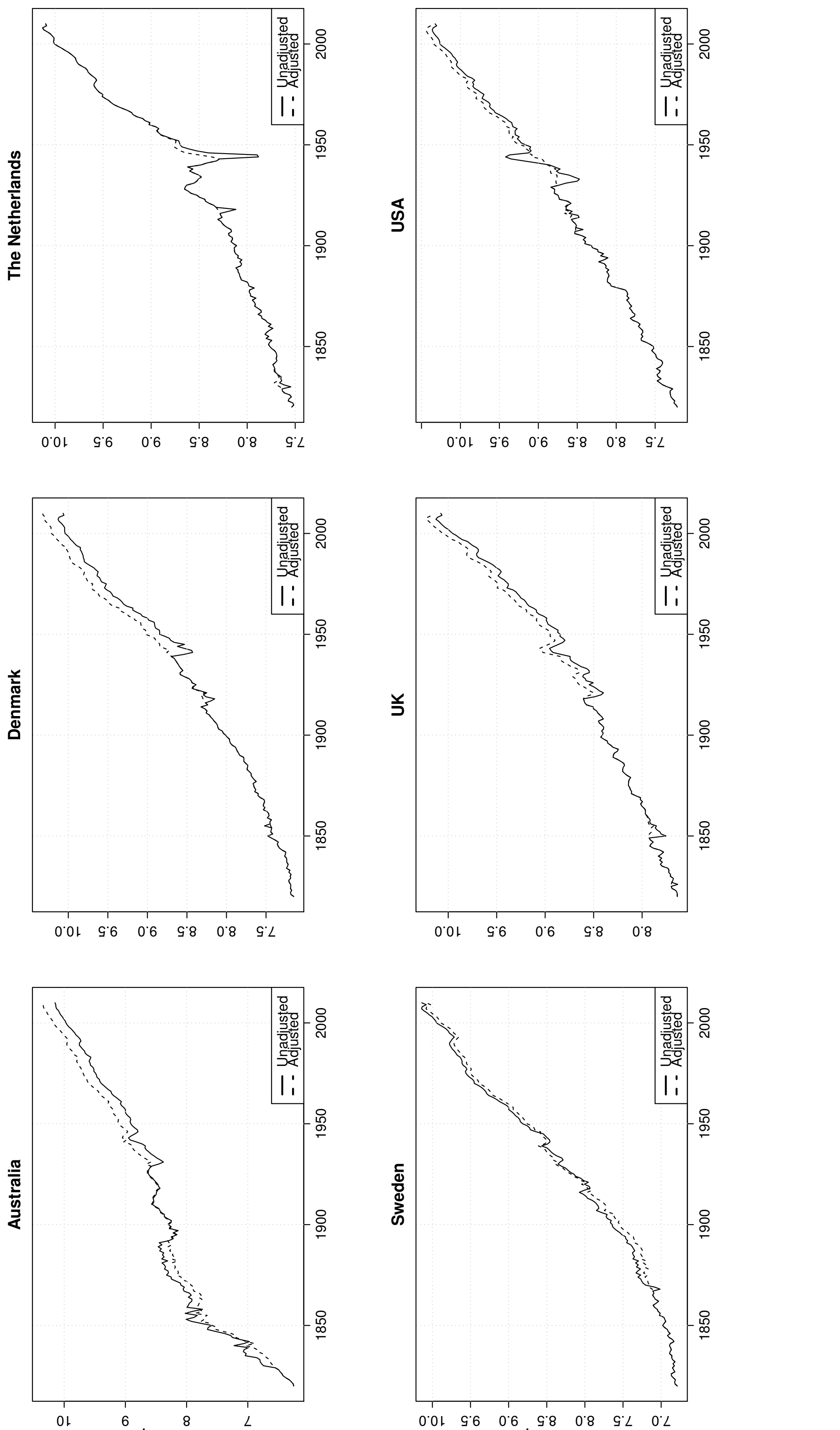
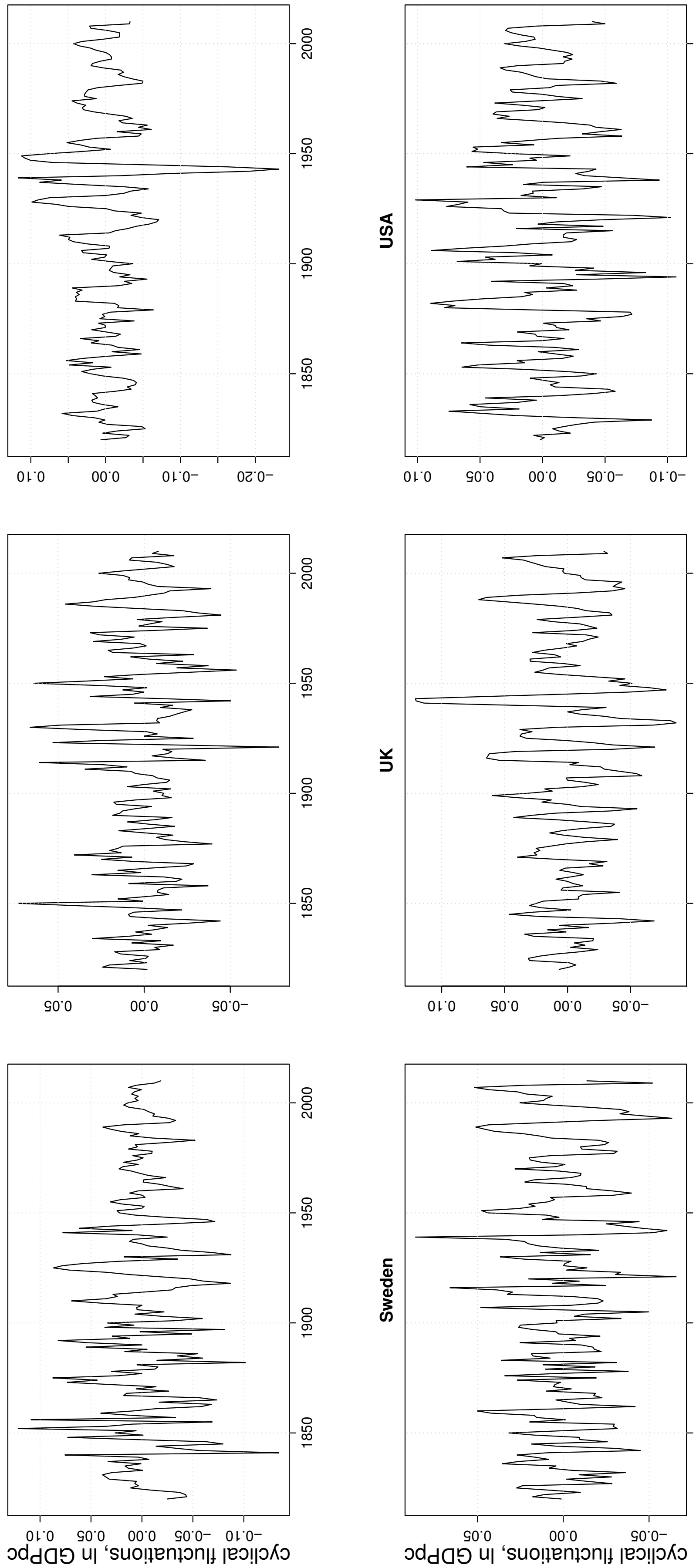


Fig. 4.5: Cycles (Kuznets) obtained with an asymmetric CF filter



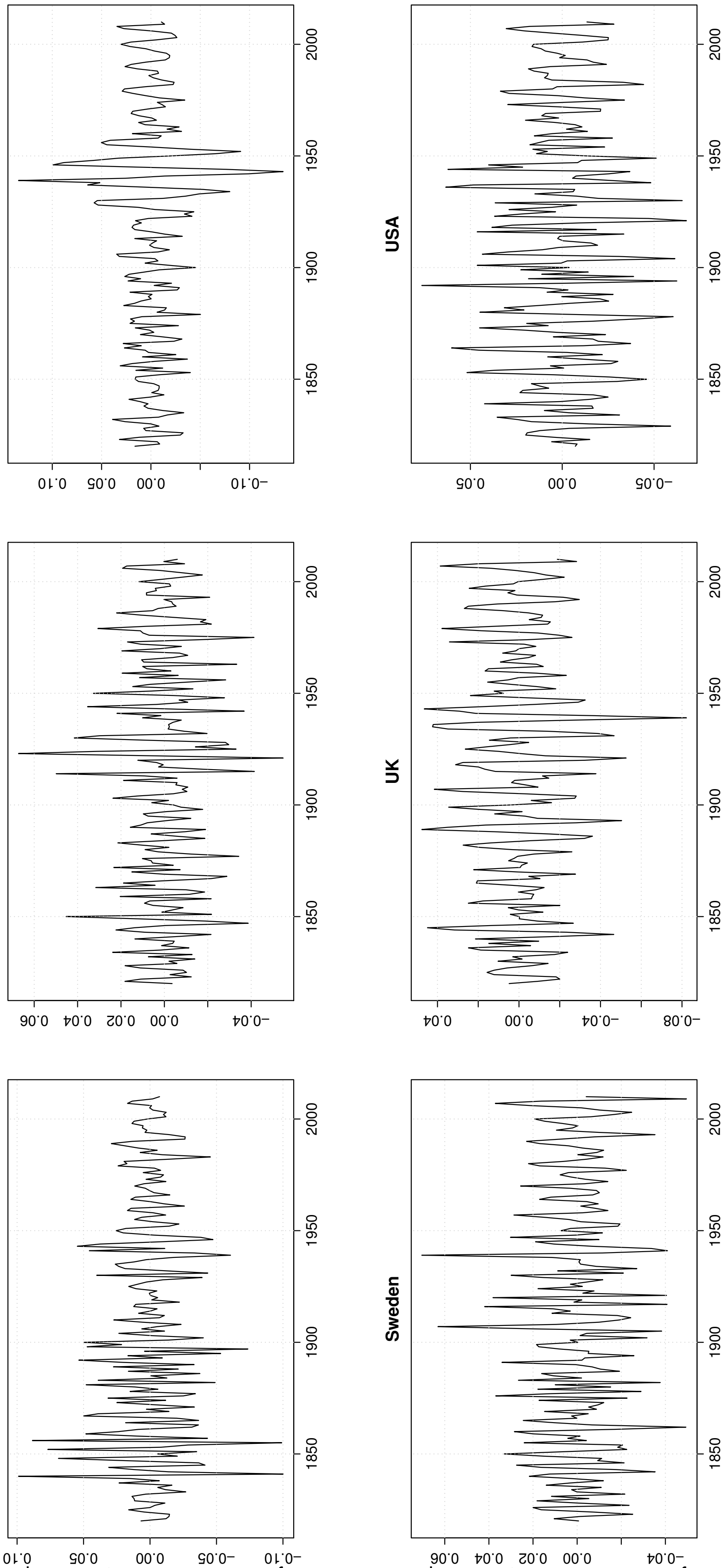
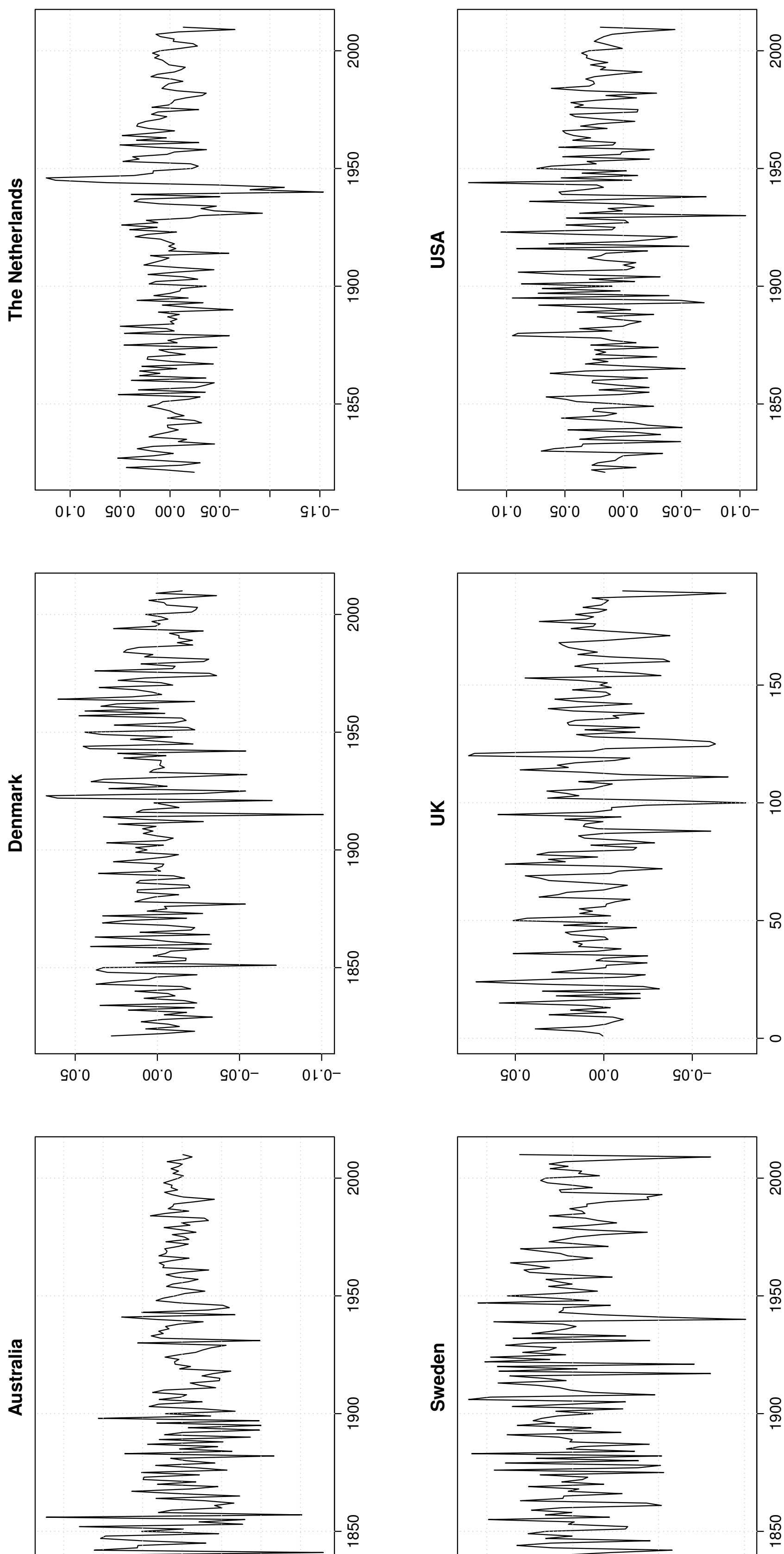


Fig. 4.6: Cycles (Juglar) obtained with an asymmetric CF filter

Fig. 4.7: Differenced (detrended prefiltered) series



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5

Discussion: overall and specific contributions

Below an overview of the overall and specific contributions is provided. These are considered in frames of the related scientific debates. In addition, specific and peripheral contributions are highlighted and a road map of further works is discussed.

5.1 Summary of the overall contributions

The most illustrative way to summarize the contributions of the above mentioned chapters, is to refer to the research agenda, posted in the general introduction of the dissertation. The first research questions, analysed in Chapter 2, were focused on the Malthusian cycles and the transition from the Malthusian to the post-Malthusian regime. Motivated by diverse aspects of the works of Crafts and Mills (2009); Galor and Weil (2000); Haines (2000); Nicolini (2007), we formulate two research questions: *whether the Malthusian effects could be present in a frontier economy and which institutions could be responsible for the Malthusian regime and the transition from it?* We have chosen seventeenth – nineteenth century Canada, in particular Quebec as an object for our analysis due to several reasons: firstly, the abundance of arable land in the frontier economies should not pose a constraint for the population development; secondly, Quebec experienced a dramatic structural and institutional change with the British conquest of 1760; thirdly, during the time frames of our analysis (1688–1860) Quebec underwent gradual economic change from a small colony with several thousands inhabitants in the seventeenth century to a developed region with several industrial centers and a network of roads, railways and river connections in the middle of the nineteenth century (for details see Geloso, 2016). Our findings show that the Malthusian cycles were present even in the frontier economy of Quebec, yet the Malthusian effects vanished with time. The structural break tests indicate one break in prices, which occurred in 1767, or seven years after the British conquest. Using the short run VAR analysis with three endogenous variables (wheat prices, death and birth rates) and two exogenous controls (war dummies and temperature deviations) we find that the pre-conquest sub-sample exhibits the positive Malthusian check (increase of death rates after an increase in prices), whereas the preventive check (decrease in birth rates after an increase in prices) was not detected. Yet, in the post-conquest sub-sample the positive check vanishes and the Malthusian cycles are not present. Bearing in mind methodological issues related to implementation of statistical filters (see Chapter 4 for details), we cross-validate our results, obtained using the filtered cycles (using the Hodrick–Prescott filter), using first differenced data. The transition was not instantaneous and the rolling estimates of standard deviation of the prices, death and birth rates had been decreasing gradually. The potential reasons for this transition are elaborated: among the possible explanations we find evidence for Smithian growth, embodied in market integration and decrease of price volatility between different parts of Canada, and institutional changes related to abolishment of seigneurial tenure and reforms of the land laws, which could act as a constraint on the usage of land. Therefore, in addition to the analysis of the Malthusian cycles, Chapter 2 highlights the role, institutions could play in the transition from the Malthusian to the post-Malthusian regime. Eventually the links between the population and economic cycles were broken down and further analyses in subsequent chapters focus rather on economic cycles. In addition, further work is conducted in order to analyse the cross-country variation in the stylized facts on business cycles.

In Chapter 3 the interaction between the cyclical fluctuations in economic and bibliometric variables are analysed using short and long-run types of analysis, namely VARs and FCVARs, therefore accounting for the long memory effects. The motivation for this chapter is embodied in the statement "panics produce texts" (Fabian, 1989) and the work of Besomi (2011), who provided a bibliometric investigation of the terms, most often used in economic literature to label crises and downswings of business cycles. Therefore, the main research question is *whether there exists an econometric evidence for the statement that "panics produce texts"*. The time frames of the analysis for different pairs of variables differ with the longest range from 1851 to 2012. The inclusion of the long memory effects in our analysis is motivated by the works of Johansen (2008); Johansen and Nielsen (2012); Jones et al. (2014), who proposed and applied models for fractionally cointegrated series. The long memory effects are related to extremely large changes of relatively long duration (Mandelbrot, 1972, pp. 259–260). The analysis with vector autoregressions (VARs) is conducted using the filtered cycles by the means of the Kalman filter; whereas, in the fractionally cointegrated vector autoregressions (FCVARs), fractionally differenced data are used. We find 18 incidents of Granger causality from economic variables to the bibliometric ones in the field of ‘Economics’[1]. Using the long-run exogeneity test, we find 10 similar cases. The analysis of the impulse-response functions allows us to conclude that the response of economic literature to a downswing of a business cycle takes up to five years. The Diebold–Mariano test suggests that forecasting bibliometric indices with economic variables is more accurate than forecasting, using only an autoregressive model. The quantitative approach to the statement that “panics produce texts” yielded findings which suggest that economic literature indeed reacts to economic cycles in the short and in the long run.

One of the main tools used in the empirical analysis of business cycles are diverse detrending methods. Therefore, Chapter 4 is focused on the methodological aspects of detrending, distortions in the spectral density and the emergence of spurious periodicities. The motivation for the given chapter was provided by the works on the spectral analysis and analysis of business cycle duration (see Cendejas et al., 2015; Diebolt, 2014; Metz, 2011; Woitek, 1997), the works of spurious periodicities (Pollock, 2013, 2014) and the works on significance testing on spectral density peaks against the related background noise from natural sciences (Mann and Lees, 1996; Thomson, 1982). The main research question in the given chapter is: *how can spurious periodicities emerge and how could one test for these?* The investigated issue is related to spurious periodicities and the Slutzky–Yule effect, or a formation of regularities from series of random shocks (Slutzky, 1927, 1937; Yule, 1927). The widespread usage of moving averages and filters, with a summation operator involved, may amplify such distortions. Yet, even detrending with first differences may distort spectral density and dampen the long range regular and irregular dependence initially present in the series. Pollock (2013, 2014) noted the caveats of detrending: filtering may amplify lower frequencies and dampen higher ones; whereas, differencing amplifies high frequencies and dampens the lower ones. The time frames for the analysis are 1820–2010. I used the well-established methodology and first adjusted the data for outliers, since these may create distortions in the low frequency range. After the adjustment different types of signals were derived: filtered signals, using different frequency bands, and differenced ones. The tests on fractional integration do not reject the null of the differencing parameter equal to one, therefore first differencing should be appropriate. After deriving the appropriate background (white or red or blue) noise, I simultaneously tested the periodicities across signals against the confidence intervals of the background noise. It turned out, that most of the low frequencies, or long periodicties, were not simultaneously significant, and thus were likely spurious. The longest periodicities, found to be simultaneously significant, were 9.6 years for the Netherlands and

[1] We analyse the data from two fields, using the JSTOR classification: ‘Economics’ and ‘Economics and business’. The latter field is broader and is merely used for cross validation.

8.348 years for the UK, which corresponds to the Juglar cycles and the findings of other researchers, investigating similar time frames. The mid-range periodicities between two and five years turned out to be simultaneously significant, whereas the periodicities attributed to the Kuznets cycles, were not, and therefore, are likely to be spurious. The results have a threefold implication: the findings related to the emergence of spurious periodicities should be considered as a warning against using the widespread rule of thumb filtering and smoothing parameters; long memory effects should be accounted for and the differencing parameter has to be estimated, prior to using differencing (whether fractional or first differencing is appropriate); simultaneous testing of spectral density peaks across different types of signals against the appropriate background noise to a certain extent can help to identify spurious periodicities, related to detrending.

The dissertation analyses diverse aspects of business cycles by means of empirical methods: the Malthusian cycles and the transition to the post-Malthusian regime, discussing the role of institutions in this transition; the interaction between economic cycles and bibliometric cycles in economics as a science. In addition, methodological aspects of the main detrending tools, used in business cycle research, are investigated in detail: the problem of spurious periodicities is analysed and a way of identifying those is proposed. Further discuss particular findings are discussed. In addition, further research and peripheral papers, which are related to the core articles in Chapters 2, 3 and 4 are considered to provide a broader view on the research agenda.

5.2 Specific contributions and further research

5.2.1 Escape from Malthusian cycles and the importance of institutions

In Chapter 2 we provided a deep discussion of the role of institutional arrangements, which could have functioned as a resource constraint. Selecting Quebec, one of the oldest Canadian provinces, as a candidate for a frontier economy, was also due to the presence of important institutional changes in its history. The British conquest of 1760 brought many new laws to the region, which were gradually introduced. One of these, was the seigneurial tenure, a restrictive land law. The process of the abolishment of seigneurial tenure started in 1790s, yet the implications of this regime echoed for a long time afterwards. The dissolution of the Malthusian check should not be solely attributed to the changes in land laws: as we noted in the discussion section 2.6 for Chapter 2, the Smithian growth and in particular, market integration could have contributed to the dissolution of the Malthusian cycles. By contributing to the debates on the presence of Malthusian effects in a frontier economy, like Canada, we open the discussion on the role of institutions and in particular land usage regulation in the dissolution of these effects. Further work has been planned in this direction.

Preliminary results suggest, that the regions, where seigneurial tenure was governing the ownership and usage of land, had higher infant mortality rates. Bearing in mind, that infants are the most vulnerable population group, the impact of restrictive land laws on the demographic situation can be analyzed quantitatively. In Arsenault Morin et al. (2015) we analyse a cross section of infant mortality of different age groups from the census of 1851: below age of one; between one and five and between five and fifteen. The analysis is performed using a zero-inflated negative binomial regression, where zeros of the data are endogenized by the means of a logit model. This allows us to deal with zero reported deaths and explain them, since absence of deaths may be related to good health; however, it may also be related to measurement issues or simply, a small size of the settlement. This analysis suggests that in regions with inherited seigneurial tenure had higher infant mortality rate: for ages below one the effect is from 43.79 to 44.89 deaths per 1000 births; whereas for the age group from one to five the effect is smaller, yet significant and is around 5.2–5.3 deaths per 1000 population of the given age group. For further age groups the effect becomes insignificant. The finding, that in areas with inherited tenure regime, infant deaths were higher, signals certain development problems of these regions. One has to note that other effects, for which we controlled our regressions, also determine infant mortality. These include wheat yield, length of growing season and population density. An anthropometric analysis of the Quebec prison records from 1790s to 1827 shows that French-Canadians from the Quebec region were also smaller than their English, Scottish and Irish counterparts of the same birth years. Therefore Arsenault Morin et al. (2017) hints at the differences in anthropometric parameters and potentially, quality of life, between the regions with the tenure regime and the other. Although certain variation in heights could be explained by genetic features, e.g., lactose intolerance, there is an economic explanation, related to low living standards and limited access to proteins relative to other areas.

These findings constitute the directions of further research of the role of institutions in the transition from the Malthusian regime to the post-Malthusian one.

5.2.2 Economic cycles and cycles in economics: "Panics produce texts"

An econometric analysis of the relation between economic and bibliometric variables, was conducted in Chapter 3. The main findings, after conducting tests for predictive Granger causality in the short run and the long-run exogeneity tests, include numerous incidents of economic variables predicting bibliometric ones: 18 incidents of Granger causality from economic variables to the bibliometric ones in the field of ‘Economics’ using the short run VAR framework and 10 cases of rejection of long-run exogeneity in the same field using the FCVAR analysis. However, other directions of predictive causality were detected: from the bibliometric variables to the economic ones and simultaneous Granger causality, when both variables exhibit predictive causality. The latter one can be related to the measurement frequency of the aggregated bibliometric data: at higher frequencies predictive causality would be easier to identify. However, the periodcials and journals have issues at different frequencies: biannual, quarterly or even every two months. Therefore, temporal aggregation helps to overcome the diversity of issuing frequencies; however, at a cost of simultaneous predictive causality. Predictive causality in the opposite direction represents a more interesting challenge: if “panics produce texts”, could the texts, under certain conditions also “produce panic”? One should note, that the term ‘texts’ is not ambiguous: in Chapter 3 we referred to articles published in international peer-reviewed journals in the field of ‘Economics’ and ‘Business and Economics’. Bearing in mind the publication lags and the lengthy review processes, the media, including newspapers, has an advantage in reacting to crises much faster. Soo (2013) and Gunn and Johri (2016) note the important role of the media sentiments and communication of the financial market information in regards to investment decisions. Once the definition of ‘texts’ is expanded, the statement about texts “producing panic” can be revisited. The influence of media sentiments on the investment decisions is an open debate; however, one could apply a similar approach from Chapter 3 to newspaper articles in the media. One of the advantages of newspapers is a higher frequency of observations: this could help to perform inference at a quarterly, or even monthly frequencies, since many economic variables are available at these frequencies. The mixed-frequency analysis, such as mixed data sampling models as in Andreou et al. (2010) with time aggregation of mixed frequency VARs with time aggregation or disaggregation as in Schorfheide and Song (2015), could be used for such inference in order to investigate the interaction between the economic variables, newspaper sentiments and scientific output. One has to note, that the content of the newspaper materials may be affected by the topics of political orientation and or topics, describing the situation abroad. Therefore, such analysis requires deeper analysis of the nature of the newspaper articles and their semantics, and cointegration between the local economic variables and the ones of the foreign countries involved, in case if the articles are related to the news from abroad.

Newspapers are not affected by the publication lags of the scientific journals and therefore their response to changing economic conditions and business cycle indicators is much faster. It is also possible that the media, and the newspapers in particular, may amplify certain news or events, increasing their impact. Further research has to be conducted in order to observe how the semantic fields of the newspaper articles are changing with the phases of the business cycles: whereas

Besomi (2011) focused on the semantics of the business cycle phases; one could also expand the list of terms, and add more terms, most often used during the boom phases of the business cycle. Another interesting question is to test the direction of predictive causality with the help of newspaper data of relatively high frequencies, since it may be possible that even if the newspaper texts are not capable to produce panic, they still may be able to contribute to it or amplify it.

Whilst in Chapter 3 the "panics produce text" statement from the literature is approached with empirical methods; other statements, or to be more precise, stylized facts on business cycles also require analytical inference. The well-established stylized facts on the business cycles and the relations between the key economic variables can be taken from Lucas (1977) and Zarnowitz (1992). Yet, the claim that these facts are universal for all countries and all time frames is debatable (see the discussion in Hendry, 1995, p. 1627). Certain evidence exists on the correlation between the labour market institutions and rigidities and the characteristics of business cycles (Gnocchi et al., 2015) and further work is planned in order to expand the institutional aspects of such analysis. The preliminary findings of Kufenko and Geiger (2015) indicate that the direction and magnitude of the relation between the changes in unemployment and inflation; inflation and output and unemployment and output are different across the OECD countries. Having found heterogeneity in the characteristics of the business cycles across countries, we identify significant institutional correlates, which could be related to these characteristics. Further findings show, that the institutional correlates are not limited to labour market institutions, such as replacement rate and unemployment benefits, but also include proxies for monetary policy, e.g. short run interest rate volatility.

5.2.3 Use and abuse of filtering in business cycle empirics: spurious periodicities

In Chapter 4 spectral distortions caused by filtering and differencing, are identified by the means of simultaneous testing for background noise. This allows identification of periodicities, which are most likely spurious. Indeed, most low frequency peaks in spectral density after filtering were not simultaneously significant for the differenced data. This fits the statement that filtering amplifies low frequencies (Pollock, 2013, 2014)[2]. On the contrary, short and mid range periodicities were in most cases simultaneously significant. The latter confirms the findings of other researchers, Bergman et al. (1998); Cashin and Ouliaris (2001); Cendejas et al. (2015); Metz (2011); Mills (2007); Metz (2011); however, for diverse time frames. Yet some researchers find longer periodicities, e.g., of 11 years for the U.K. (Metz, 2011) – in the given chapter the longest periodicity, which was simultanously significant was around 9.6 years. The simultaneous testing in Chapter 4 provides

[2] Also see Nelson and Kang (1981) for similar findings on detrending with a regression on time.

insights into identification of methodologically driven spurious periodicities. However, there are two important aspects to consider: first aspect, is the fact that with real data the true periodicity is unknown: a simulation with a known periodicity is needed to confirm that spurious periodicities, not predefined by the simulation design, emerge after detrending; second aspect is that the longest band of the CF filter in Chapter 4 is set to 25 years, approximating the upper bound of the Kuznets cycles; therefore, leaving the Kondratieff waves out of the research scope.

The usage of real world data is always accompanied with a number of challenges and the cliometric nature of the series adds additional issues: for example, the compatibility issue, e.g., if the data had been compiled from different sources for different periods or the aliasing effect (Priestley, 1981, p. 224), a discrepancy resulting from discrete measurement of continuous processes, or the sample size, since for spectral analysis at least 100 observations are required (König and Wolters, 1972, p. 83). In Chapter 4 cliometric data was used, with 191 observations at an annual frequency. The outlier adjustment can potentially deal with structural breaks and shocks, yet there will always be room for an error. 191 observations may be sufficient; however, these had been taken at an annual frequency and cover a very large time span in history. Therefore, statistical exercise in necessary in order to see how spectral distortions emerge and manifest themselves in the spectral density of the filtered series. For these purposes simulated data suits well, since in case if the built-in frequency (or periodicity) of a sinusoid is known and disturbances are added, one may see whether (and how) a filter is amplifying low frequencies inside of the bands. As a model for simulations, one can appeal to the Solow (1956) model since the data used in Chapter 4 represent long-run output trajectories.

$$k_{i,t+1} \approx s_i y_{i,t} + (1 - \delta - n_i) k_{i,t} \quad , \tag{5.1}$$

$$y_{i,t} = k_{i,t}^{\alpha} + c_{i,t} \quad , \tag{5.2}$$

where on *per capita* basis, $y_{i,t}$ is output, $c_{i,t}$ is the cyclical component, $k_{i,t}$ is capital, s_i is the saving rate, n_i is the population growth rate, δ is the depreciation rate, α is the elasticity of output with respect to capital, i and t are country and time subscripts.

The following parameters for the Solow model are set arbitrary in a similar fashion as in Kufenko and Prettner (2016) in order to ensure a strong trend: s_i variates from 0.2 to 0.75 with a mean of 0.45 and standard deviation of 0.09; n_i variates from 0.0004 to 0.05 with a mean of 0.025 and standard deviation of 0.01; the initialization, or random k_0 for each country is set to be less than 0.2 or 20% of the steady state. The cyclical component is simulated as follows:

$$c_{i,t} = A \cdot sin(B \cdot t) + V\varepsilon_{i,t}, \tag{5.3}$$

where A is the amplitude, B is the periodicity, t is the time index, V is the scale parameter for noise, $\varepsilon_{i,t}$ is white noise.

For the simulation we set the periodicity B to 0.3141, which correpsonds to a quasi-Kuznets cycle length of 20 years; the amplitude A of the regular fluctuations is set to a relatively low value of 0.4, so that the given periodicity would not be easily detectable at the first glance; the scale of white noise, V, is set to 6. The main goal of the simulations is to create such a process, in which a relatively long frequency would be *hidden* and noise would prevail.

The benchmark process has a distinct trend, with a non-linear shape (see Fig. 5.1). I simulate 200 observations, close the length of the series used in Chapter 4. Now the bands of the CF filter are set to conventional 8 and 3 years in order to test which distortions can arise if relatively long periodicities are *hidden* in the series. The 50 simulations[3] with white noise disturbances from the a normal distribution (see Trautmann et al., 2014) are shown on Figure 5.1. Figure 5.2 displays spectral density estimates using the same methods as in Chapter 4 (Blackman–Harris window with 7 segments and 50% overlapping). The spectral density peaks are observed at 4 and 7 years: the smaller peak at 7 years can be attributed to the longer periodicity, *hidden* outside of the filtering bands; whereas, the larger one at 4 years is most likely related to the inclusion of white noise shocks and the Slutzky–Yule effect. It appears that spurious peaks emerge in the vicinity of the upper bound, as well as in the range of higher frequencies. Although the experiment is somewhat unfair because of the fact that the periodicity lies outside of the bands, it is a realistic situation, since in the reality even whilst using a raw periodogram it is hard to set the filtering bands appropriately.

Such statistical artifacts urge for significance testing against the background noise and further Monte Carlo simulations. Considering Chapter 4, the research question can be expanded to the analysis of spurious filtering with the help of diverse simulated processes and scenarios. In addition to univariate distortion, multivariate distortions and emergence of spurious dynamic relations after filtering (see Hamilton, 2017) is of particular interest for future research.

[3] Conducting more simulations is technically feasible; however, for proper graphical representation, 50 appears to be optimal.

Fig. 5.1: Simulated benchmark process (Equation 5.2)

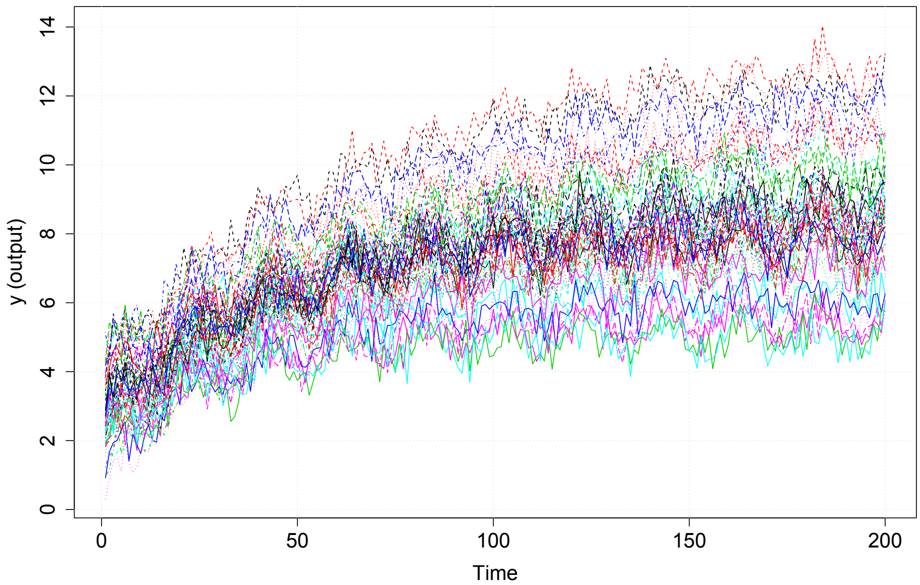
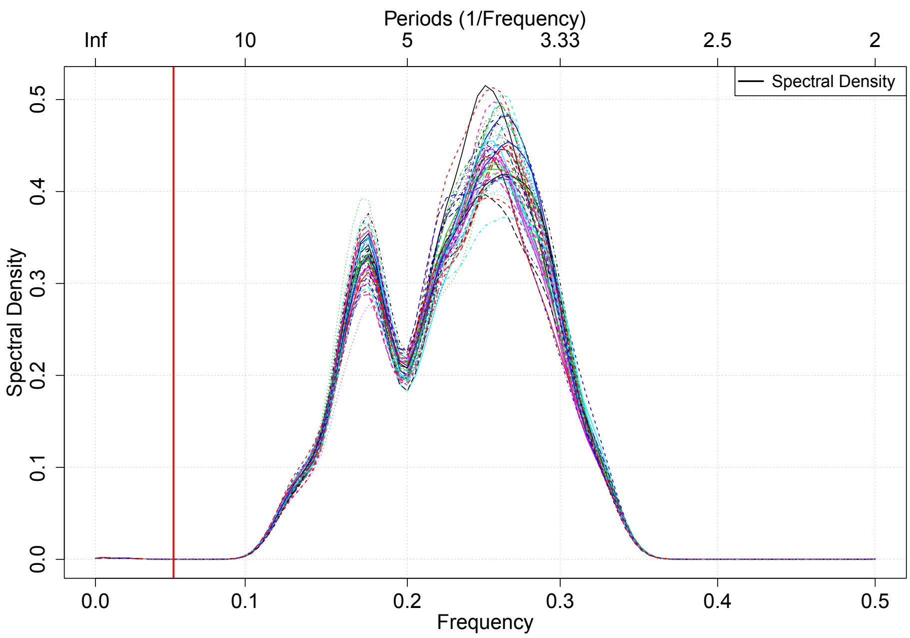


Fig. 5.2: Spectral density of the filtered simulated benchmark process. Solid line denotes a built-in periodicity of the simulated cyclical component.



It is also important to briefly discuss the potential presence of periodicities longer, than the ones of the Kuznets cycles. Although the analysis of such periodicities requires different methods, this aspect hast to be addressed as well, bearing in mind the Reijnders (1990) on the long waves and their detection in economic series. In the latter work, the methods and results of Kondratjew (1926) and Kuznets (1930) are explained in detail and compared (Reijnders, 1990, pp. 254–262). Although the author is presenting evidence for existing of the Kondratieff long waves, he does it with due diligence, elaborating of the 'aliasing effect', an artifact related to discrete measurement of the continuous process, already mentioned before; 'perspective distortion', an effect emerging, if the duration of the cycle exceeds the size of the measurement window (Reijnders, 1990, p. 137) and the Slutzky–Yule effect, also mentioned before (Reijnders, 1990, p. 75 and pp. 247–252). In addition, several methods are proposed for analysing long waves, e.g., standardization in order to correct for the 'perspective distortion' effect (Reijnders, 1990, pp. 200–202). Another work on the empirical analysis of the long waves, worth noting is van Duijn (1983).

After having summarized the main research questions posted in the introduction and the answers to them, embodied in the findings from Chapters 2, 3 and 4, additional aspects of the issues in consideration and potential directions of further research were discussed. The concluding remarks provide a detailed overview of the findings in a broader context of the related scientific debates and of the dissertation as a whole.

6 Summary and conclusion

The summary and conclusion summarizes the main findings and draws attention to the contributions of the dissertation to the related scientific debates. In general, the last 50–60 years have been fruitful in terms of empirical and theoretical research output on business cycles. Bearing in mind that before 1950s the term 'trade cycle' was predominantly used do describe the economic fluctuations, the history of business cycle research is considerable longer and goes back to the works of Juglar (1862) and Kitchin (1923). However, the role of institutions in an economy is a somewhat younger topic, which could be traced back to the works of North (1991). Yet the merger of these two topics, business cycles and institutions, offers fruitful grounds for new research and in particular, empirical analysis. In the given dissertation business cycles and institutions are considered in transition, in order to show that institutional arrangements may form economic constraints or build-up on the existing ones, responsible for the regimes in which cyclical fluctuations take place; the interaction between the economic cycles and research output in the sphere of 'Economics' and 'Economics and Business' is analyzed, to empirically test whether the phases of cycles stimulate more publications on the topic of business cycles and related; and the caveats of the main detrending methods, involved in the empirical business cycle research, are investigated to analyze the emergence of spurious periodicites and the possible way of testing for them.

One of the most fascinating examples of a transition from one regime of cycles to another one is the change from the Malthusian cycles to the post-Malthusian ones (Chapter 2). In a Malthusian regime, population cycles are interlinked with economic cycles, or to be more precise, price cycles (Commons et al., 1922). These interlinks formed due to contemporary constraints, manifested themselves in the so-called Malthusian checks: the positive check, or the direct relation between prices and death rates, and the preventive check, or the inverse relation between prices and birth rates (for details see Crafts and Mills, 2009; Fertig and Pfister, 2012; Galloway, 1988; Nicolini, 2007). Whereas most works consider Western Europe, small frontier economies, with an abundance of land and a relatively high land-to-labour ratio (Álvarez Nogal and Escosura, 2013), are not broadly covered. The existence of Malthusian cycles in such cases would hint on the presence of certain constrains on land availability, yet not necessary of a purely physical nature. Quebec was selected as an object of the analysis due to this reason. In addition, during the time frames of analysis 1688–1860, Quebec experienced an institutional change with the British conquest of 1760. This change constituted numerous amendments to the existing laws, including land legislation, and introduction of the new ones. Our research question, formulated for Chapter 2, was the following: *whether the Malthusian effects could be present in a frontier economy and which institutions could be responsible for the Malthusian regime and the transition from it?* The first question is dealt with by the means of structural break tests, VARs with exogenous control and Granger causality testing. The only structural break clearly identified in the series of wheat prices was in 1767, or seven years after the British conquest of Quebec. This allows us to separate the data sample into the pre- and post-conquest periods. Our findings suggest that the Malthusian checks were present only in the pre-conquest period (1688–1767), whereas in the post-conquest period and up to the end of our observations (1860) the Malthusian effects were not detected (see Tables 2.7 and 2.8). Bearing in mind issues related to detrending methods (see Chapter 4), we validate the results obtained from the filtered data by estimating the equations using the differenced data. We observe two forces, which could potentially contribute to the transition to the post-Malthusian regime: the gradual change related to Smithian growth and the institutional changes, related to revision of land laws, including the abolishment of seigneurial tenure after 1790s. The first argument can be supported by rolling estimation of the standard deviations of the series and spreads between regional wheat prices: the volatility of prices and price spreads have been gradually decreasing since the beginning of the eighteenth century. The role of institutional change is discussed in detail, motivating the authors for further research: Arsenault Morin et al. (2015) we show that the regions with the tenure law had significantly higher infant mortality, after controlling for wheat yield, length of growing season, population density and other effects; whereas, in Arsenault Morin et al. (2017) we find evidence, that the convicts, born in the regions, which had tenure laws in the past, were smaller than their counterparts from other areas. This research will be continued in order to provide more insights on the role of institutions in the dissolution of the Malthusian cycles and the subsequent transition to the post-Malthusian regime.

After the demographic transition the dissolution of the link between the population dynamics and economic cycles took place (see Galor, 2005; Galor and Weil, 2000). Therefore, the subsequent research questions were rather focused on the analysis of business cycles. The interaction between economic variables and research output in ‘Economics’ as a science is another insight in the far reaching consequences of the downswings of business cycles. Motivated by the work of Besomi (2011), who proposed a list of terms, most frequently used in economic literature to describe phases of the business cycles, we approach the statement of Fabian (1989) that "panics produce texts" with the help of econometric tools for short- and long-run analysis. Whereas in Chapter 2 predominantly short run VAR framework had been used for the predictive causality testing; in Chapter 3 we also include the FCVAR analysis, allowing for long memory effects and fractional cointegration. The application of FCVARs with fractional differencing is also related to the fact, that filtering, used for the VAR analysis, may produce spurious periodicities. In the FCVAR framework we perform long-run exogeneity testing, which, in regards to our research question, is complementary to the short run Granger causality testing. Our main research question for Chapter 3 is *whether there exists an econometric evidence for the statement that "panics produce texts"*. Our sample consists of 14 bibliometric variables and two indices (downswing and overall) of relative frequencies of the terms from Besomi (2011) and seven economic variables measured for different periods, ranging from 1851 to 2012. We find 18 incidents of predictive causality from the economic cycles to bibliometric ones in the field 'Economics', which largely validates our hypothesis for the short run analysis. The impulse-response functions suggest that the response of bibliometric variables to economic shocks takes from one to five years. The FCVAR analysis for fractionally cointegrated series yielded ten similar incidents, based on the long-run exogeneity test. The Diebold–Mariano test shows significant improvements in the forecast quality of the bibliometric variables, once economic ones are included in the model. Yet other directions of predictive causality had been found: instantaneous one and the one from bibliometric variables to the economic ones. Whereas the first one could be attributed to the frequency resolution, since the measurements had been done at an annual frequency, however, the response of science to the contemporary economic situation may occur at higher frequencies; the second direction of predictive causality endorses further investigations. Since Gunn and Johri (2016) highlight the role of news from the financial markets in decision-making of economic agents, these investigations can be carried out using newspaper sentiment indices, based on the terms used in Chapter 3: newspapers tend to react to the changes in economic reality at higher frequencies and they have a broader auditory. Therefore the statement "panics produce texts" could be revisited for the media. Another well-established general statement about the business cycles is that the stylized facts related to economic fluctuations are universal (see Lucas, 1977). Few works exist on the relation between certain characteristics of business cycles and institutions (e.g., see Gnocchi et al., 2015, with regards to labour market institutions). The preliminary findings of Kufenko and Geiger (2015) show that the direction and magnitude of the relations between key business cycle variables (inflation, unemployment and output) significantly differs across the OECD countries. Moreover, the magnitude of these relations correlates with certain institutional variables, such as replacement rate and unemployment benefits, but also proxies for monetary policy, e.g. short run interest rate volatility.

The empirical research of business cycles is performed using diverse statistical and econometric tools. Among these are the detrending methods, used to separate cycles from a trend. Among the detrending methods, one should highlight filtering and differencing. However, both methods can potentially distort the spectral density of the data and create spurious periodicities. In particular, the settings of the statistical filters, e.g., the smoothing parameters or and their usage as a rule of thumb, could lead to the emergence of such artifacts. The emergence of spurious periodicities from random walks after application of moving averages, is just one of such examples of potential distortions (see Nelson and Kang, 1981; Slutzky, 1927, 1937; Yule, 1927). Yet, few research explicitly deals with identification of spurious periodicities in the spectral density (Pollock, 2013, 2014; Woitek, 1997). The latter works, as well as the works of spectral analysis of cliometric series (including Diebolt, 2014; Cendejas et al., 2015; Metz, 2011) and the methods of significance testing of the spectral density peaks (Mann and Lees, 1996; Thomson, 1982). In order to answer the research question of Chapter 4: *how spurious periodicities can emerge and how could one test for these?* I used cliometric data on output during 1820–2010 for six countries and perform spectral analysis with simultaneous significance testing against noise to reveal the periodicites, which are most likely spurious. In the beginning the outlier adjustment was performed and the the differencing parameter was estimated to test whether first differencing is appropriate. Afterwards two types of signals were derived, namely filtered and differenced ones. The upper bands for filtering resemble the Kuznets (25 years) and the Juglar cycles (eleven years). In addition, the appropriate background noise (white, red or blue) was derived and simultaneous significance testing across signals against the noise was conducted. The findings suggest that most of the mid- and high-range frequencies were simultaneously significant; however, the peaks at low frequencies were not: the longest periodicity, to be simultaneously significant was around 9.6 years, which corresponds to a Juglar cycle. The research could be continued using simulated data, with a know dominant frequency. It can be shown (see Section 5.2.3 and Fig. 5.2) that in presence of a cyclical component wtih random disturbances, under certain conditions filtering amplifies frequencies, which are not implicitly built-in in the simulation, therefore creating spurious peaks in spectral density, close to the cut-off bands. The findings from cliometric and simulated data urge for further simulations in order to assess the efficiency of filters, elaboration of simultaneous significance testing of the spectral density peaks and avoidance of the usage of rule of thumb parameters for filtering.

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