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Dating business cycle turning points: The Greek economy during 1970-2012 and the recent recession

by
Ekaterini Tsouma*

This paper establishes a reference chronology for the Greek business cycle from early 1970 to late 2012, against the backdrop of the late 2000s global recession and the most recent domestic economic developments, which once again stress the significance of dating business cycle turning points. The derivation of the exact dates of switches between expansions and recessions allows the identification of the point in time at which the Greek economy entered the recent recessionary business cycle regime in the late 2000s and the verification of the assertion that, up to the end of 2012, it had not yet exited the recession. We rely on both non-parametric and parametric procedures in order to check the coherence among the obtained turning points and evaluate the establishment of a reference chronology. We use quarterly GDP data and selected monthly indicators covering important sectors and activities in the Greek economy. On the basis of the obtained exact turning point dates and the indications provided by several business cycle and phases characteristics, we are able to propose a reference chronology for Greece and outline stylised facts of the Greek business cycle for a time period of over 40 years. Our findings clearly suggest that the Greek economy entered a recessionary business cycle regime in 2008 which was continued throughout 2012.

Keywords: Business cycle turning points, dating algorithms, recession, Greece

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1. Introduction

The significant worldwide downward fluctuations in cyclical economic activity recorded during the late 2000s revived the interest in the analysis and measurement of the recurrent but not periodic fluctuations in overall economic activity, that is, business cycles. According to the classical business cycle definition by Burns and Mitchell (1947), expansions and recessions are pictured as the two distinct phases of the business cycle. Within this context and as witnessed by the latest economic developments, business recessions, described as significant declines in the level of economic activity, still constitute a major issue with a negative impact on the course of aggregate economic activity. There are several dimensions as to the significance of economic recessions, such as duration or depth, but great importance is also attributed to the exact timing of the beginning and end of a recessionary regime. More generally, the exact dating of business cycles and their phases continues to possess a central role for a variety of reasons. Intuitively, any reliable knowledge concerning the state of the economy is particularly useful to individuals, institutions, enterprises and not least public authorities. On a more technical level, the dating of expansions and recessions is related to various empirical applications such as economic series' classification according to their timing or forecasting exercises.

In practice, business cycle dating is a common exercise applied to derive the so-called business cycle reference chronology, which is given by the grouping in time of the switches, or turning points, describing the limits or boundaries of business cycle phases. For the USA, experts at the US National Bureau of Economic Research (NBER) provide with considerable historical continuity and on the basis of consensus the business cycle reference chronology for the US economy. This established chronology is mostly regarded as a standard and constitutes the point of reference for any research on the dating of the turning points in general US economic activity. Nonetheless, in most countries official dating institutions are absent. In addition to the fact that the derivation of a business cycle reference chronology is not self-evident, dating is hampered by difficulties relating to data availability and reliability.

In the case of Greece, the following considerations regarding the most recent adverse developments in economic activity render the issue of dating the Greek business cycle a matter of outmost importance: the general assertion that the country is undergoing a sixth year of recession at the beginning of 2013 and its implications; as well as, the timing of a potential and long awaited turn in economic activity, which would signal the exit from this specific business cycle regime. The motivation to exactly date expansions and recessions in aggregate economic activity in Greece over a long period of time is significantly reinforced by the fact that there is very little relevant research done and that, in addition, there is no official reference chronology to rely upon. The related investigations are conducted almost unexceptionally within the context of the establishment of individual or aggregate chronologies for the European Union and euro area countries.

With the aim to fill this gap, the present work attempts to derive accurate and robust business cycle dates for Greek economic activity, over a long historical time period, in order to establish a reliable reference chronology. A variety of non-parametric and parametric procedures are employed for the dating of the Greek business cycle, and the emergence of a consensus on the exact turning point dates is evaluated. To the best of our knowledge, no similar dating applications can be found in the related empirical literature comparatively applying non-parametric and parametric procedures for dating the Greek business cycle in order to derive a reference chronology.¹

In this work, we apply a simplistic “consecutive quarters of negative GDP growth” rule,² the non-parametric Bry and Boschan (1971) procedure and related non-parametric algorithms introduced by Harding and Pagan (2002, 2006a), as well as the parametric Markov-switching model to identify Greek business cycle turning points. This comparative exercise provides the advantage of avoiding reliance on a single procedure or algorithm and further allows facing the argument of inadequacy of the use of any single series, such as GDP³ or IP. The latter is achieved through the incorporation of information contained in multiple single economic time series for the Greek economy. The time period under investigation begins in January 1970 (or the first quarter of 1970 for quarterly data) and ends in December 2012 (or the fourth quarter of 2012 for quarterly data).

The results imply a striking coherence among the obtained dates, indicating that the application of distinct methods leads to very similar outcomes regarding the exact timing of economic fluctuations in Greece over the past four decades. This allows the derivation of a robust business cycle reference chronology for the Greek business cycle, which proves consistent with widely accepted historical stylised facts across a time period of over 40 years. On the basis of the identified turning points, reference is made to specific business cycle characteristics and internationally established business cycle features, such as asymmetry between expansions and contractions. With reference to the issue of the Greek economy entering a recessionary regime in the late 2000s, the evidence clearly confirms that Greek economic activity is undergoing a recession since 2008 and based on the information up to December 2012 (or the fourth quarter of 2012) there are no signs of an exit from the contraction.

The rest of the present paper is organised as follows. Section 2 offers a short review of the related literature. Section 3 presents the underlying data and introduces the applied dating procedures. Section 4 provides and discusses the results. Section 5 concludes.

2. Literature review

In the business cycle literature, empirical applications on dating business cycle turning points are not scarce, even though mostly concentrated on the USA and other advanced economies. A considerable part of the relevant literature applies the dating of business cycles to specific country zones or groups, such as the European Union or the euro area, and the establishment of business cycle chronologies is often related to the question of cycle synchronisation. In general, dating applications aim at providing alternative and/or comparative chronologies in the few cases of existing official business dating authorities, while in the cases of lacking business cycle dating committees, the existing applications provide the only sources of concrete reference to the exact dating of turning points.

Despite their common purpose, business cycle dating applications often vary in terms of several factors, such as the underlying concept of the business cycle itself, employed data bases and frequencies or applied methodologies. Business cycle chronologies rely on the concept of the classical cycle or, alternatively, the growth cycle and result out of the use of single or, alternatively, multiple series on a quarterly or monthly basis. Industrial production, GDP and unemployment data belong to the most commonly used series for business cycle dating, whereas data sets of other macroeconomic variables and composite indicators are also employed. Dating applications to country zones or groups also rely on aggregated data.

The variety of underlying methodologies ranges from simple ad hoc rules⁴ or even graphical inspection to sophisticated parametric applications. Among these methodologies, the popular NBER dating procedure provides the basis for numerous applications. At the same time, it faces criticism on the grounds of being non-transparent or reproducible and subject to significant delays in announcements (see, for example Chauvet and Piger, 2003).

Alternative procedures for business cycle dating are characterised by greater transparency and consistency, by relying on formal algorithms, which mostly involve automated procedures or statistical models. The original Bry and Boschan (1971) (BB) automated algorithm and its later modifications and/or extensions for business cycle dating belong to the category of most popular procedures applied in the related literature mainly for advanced, and in fewer cases for developing economies, but also for country zones or groups. Among such applications are: Artis et al. (1997) for the G7 and most major European countries; Christoffersen (2000) for Finland, Norway, Sweden and Denmark; Artis (2002), who uses an algorithm related to the BB procedure for Great Britain; Biscarri (2002)⁵ for a group of 14 European countries and the US; Mönch and Uhlig (2005) for the euro area;⁶ Rand and Tarp (2002) for a sample of 15 developing economies (in Africa: Côte d'Ivoire, Malawi, Nigeria, South Africa, Zimbabwe; in Latin America: Chile, Colombia, Mexico, Peru, Uruguay; in Asia: India, Malaysia, Morocco, Pakistan and South Korea); Du Plessis (2006) for a group of selected developing economies (Hong Kong, Israel, Korea, Mexico, Peru, the Philippines and South Africa); and, Arango et al. (2008) for Colombia.⁷ The quarterly version of the BB algorithm (BBQ), according to Harding and Pagan (2001), is used in a number of studies such as Bodart et al. (2003) and Bodart et al. (2005) for Belgium; Krolzig and Toro (2005) for a subset of six EMU member countries; Morley and Piger (2005) for the USA; and, Harding and Pagan (2001) for the euro area.

Within the class of parametric procedures for business cycle dating, the basic Markov-switching (MS) model, as well as modifications and extensions (e.g. multivariate MS model, MS-dynamic factor model (DFMS)) are applied to identify business cycle turning points. Among such parametric applications are Bodman and Crosby (2000) for the Canadian economy; Chauvet and Piger (2003) for the USA;⁸ Watanabe (2003) for Japan; Chauvet and Piger (2007) for the USA; Chauvet and Hamilton (2005) for the USA;⁹ Artis et al. (2004a) for nine European economies; and, Krolzig (2001) for the euro area business cycle.

In many cases of business cycle dating empirical applications, comparative exercises which use multiple procedures are considered more preferable, with the results mostly suggesting significant coherence among the obtained turning points. Such studies, using different dating procedures, are Boldin (1994) for the US business cycle;¹⁰ Layton (1996) and Layton (1997) for the USA and Australia; Bonenkamp et al. (2001) for the Netherlands;

Harding and Pagan (2002) for the USA;¹¹ Layton and Banerji (2003) for the USA; Bruno and Otranto (2004) and Bruno and Otranto (2008) for Italy; Schirwitz (2009) for dating the German business cycle; Bodman and Crosby (2005) for the G7; McAdam (2007) for the US, Japan and the euro area; Bengoechea and Perez-Quiros (2004) for the euro area; Anas et al. (2007) for the euro area; Billio et al. (2007) for the EU15; Chen (2007) both for individual EMU countries (with the exception of Greece, Luxemburg and Ireland) and the euro area aggregate; and, Medhioub (2009) for Mediterranean countries (France, Italy, Greece, Spain, Tunisia and Turkey).¹²

3. Data and methodology

The main focus of the present work is the establishment of a robust reference chronology for the Greek business cycle,¹³ and the detection of clear evidence on the Greek economy entering the recent recession in the late 2000s and still undergoing a recessionary regime up to the end of 2012. In order to reinforce the robustness of the chronology, we first choose a sufficiently long time period for the dating of the Greek business cycle in order to control the verification of widely accepted historical stylised facts. We rely on both aggregated quarterly and constructed monthly GDP data, as well as monthly individual economic series in order to compare turning point dates derived from data of different origin. At the same time, we apply various dating procedures to deal with issues relating to the alleged arguments of simplicity, non-formality or subjectivity of methodologies and be able to base independency from the applied procedure on consistency in the obtained dates. In addition, we use the obtained reference chronology to investigate specific business cycle characteristics and evaluate their accordance with internationally well-established business cycle features.

3.1. Data

Aggregate data series, such as GDP, which summarise economic activity, are undoubtedly appropriate for the derivation of a reference chronology.¹⁴ To exploit this advantage, we use quarterly GDP data (at constant prices), taken from the quarterly national accounts. For comparison, and in order not to rely solely on signals from quarterly GDP data, we further employ selected single monthly series for both the derivation of a monthly GDP series through interpolation and the identification of specific cycles' chronologies in individual monthly series to be used in turning point aggregation. The underlying monthly individual series, which are chosen for being representative of significant broad sectors and activities in the Greek economy and, hence, reflecting the corresponding cyclical movements are: (a) the Industrial Production Index, taken from the OECD Main Economic Indicators Database; (b) the Turnover Index in Retail Trade which is deflated; and, (c) the value of imports (arrivals) which is deflated and indexed.¹⁵ All series are seasonally adjusted. The time period considered for dating the Greek business cycle begins in January 1970 (1970Q1) and ends in December 2012 (2012Q4).

3.2. Dating methodologies

In the present work, we apply different dating procedures in order to determine business cycle turning points in Greek economic activity. This comparative exercise is considered more preferable than the selection and application of a single procedure, and forms the basis for evaluating the emergence of a consensus on the exact turning point dates. More specifically, in a first step we apply a simple "quarters of GDP growth" rule of

thumb. Then, three formal algorithms translating the essence of the definition of business cycles according to Burns and Mitchell (1947) are used, which are based on automated procedures. Even though these procedures involve a certain degree of judgment because they underlie a number of subjective choices, they are by their construction, characterised by replicability and transparency. The first algorithm is the BB procedure, which is applied using a constructed monthly GDP series. The second is the quarterly BBQ algorithm and it is used on the basis of quarterly GDP data. The third is based on the individual determination of specific turning points in single economic series by the use of the BB procedure in order to derive an aggregate reference business cycle chronology by applying the algorithm according to Harding and Pagan (2006b). In a final step, the Markov switching model for business cycles is applied, with the aim to avoid any ad hoc subjective choices. In this model, turning points are directly inferred through the obtained recession probabilities, since they are treated as structural events inherent in the data generating process (see Kim and Nelson, 1999). This parametric procedure has the advantage that it can capture asymmetry in business cycle fluctuations.

Having obtained five chronologies by the application of five dating procedures, consistencies and discrepancies in the derived peak and trough dates are discussed, and the underlying methodologies are evaluated. On the basis of the significant coherence and consistency observed in the resulting turning points, a quarterly reference business cycle chronology is established for the Greek business cycle and a time period of over 40 years. The identified chronology is then used for reference to specific business cycle characteristics. Several related stylised facts are further discussed, in particular with reference to some features of the latest recessionary regime the Greek economy is still undergoing.

(a) Simple GDP growth rule

In a first step, a simple ad hoc rule imposed on GDP growth is used in order to identify turning points in the Greek business cycle. The applied rule, which is asymmetric, is based on the popular notion of “consecutive quarters of negative growth” for recession identification (and correspondingly, consecutive quarters of positive growth for expansion identification). More specifically, for the location of a peak, we require that three or three-out-of-four of the quarters that follow are characterised by negative GDP growth; for the identification of a trough we require that two or two-out-of-three of the quarters that follow are characterised by positive GDP growth.¹⁶

(b) Bry-Boschan procedure with monthly GDP series

We apply the non-parametric automated procedure introduced by Bry and Boschan (1971) for classical cycle turning points detection, on the basis of monthly economic series. Note that this specific algorithm basically replicates the expert system developed at the NBER for identification of business cycle turning points and codifies the procedures applied by Burns and Mitchell (1947). The key element of this approach consists of determining the chronology of the phases of the business cycle by the location of the exact switch points from an expansion to a contraction and vice versa. This is achieved by identifying local minima and maxima in the path of the underlying economic series, on the basis of a general rule, so that a peak and a trough, respectively, are given if

$$\{y_t > y_{t-k}, y_t > y_{t+k}, k = 1, \dots, M\}, \quad (1)$$

$$\{y_t < y_{t-k}, y_t < y_{t+k}, k = 1, \dots, M\}. \quad (2)$$

In technical terms and as Bry and Boschan (1971) formulate it, “the programmed approach operates through a preliminary determination of cycles and a gradual narrowing down of neighbourhoods within which turning points are selected. The process involves several weighted and unweighted moving averages of varying flexibility”.¹⁷ Watson (1994) provides a program implementation of the BB business cycle dating algorithm.¹⁸ In order to follow the basic principles of the Burns and Mitchell dating procedures, M is set to 5 for monthly data. At the same time, specific censoring rules¹⁹ are also imposed, which refer to the elimination of local turns, and specific constraints on phase and cycle durations.

The application of the monthly BB procedure requires the use of monthly data series, and hence, we resort to the method of interpolation due to the lack of monthly Greek GDP data. We use the Chow and Lin (1971) interpolation method, which presents a prominent procedure for interpolation²⁰ and relies on the idea of deriving a monthly measure for GDP on the basis of information contained in related higher frequency economic series. In other words, both quarterly GDP data and monthly data on related economic series are used to estimate a monthly GDP series, by regression on the respective series to obtain the best linear unbiased estimates of the monthly GDP series.

(c) Quarterly Bry-Boschan procedure with quarterly GDP data

In the next step, we apply the BBQ algorithm, according to Harding and Pagan (2002, 2003a), with quarterly GDP data. This procedure, which relies on a quarterly version of the programmed implementation of the BB censoring code by Watson (1994), can be seen as a simplification of the BB procedure (see Harding and Pagan, 2003a, p. 3). An algorithm for the implementation of the BBQ algorithm is provided by James Engel.²¹

As is the case for the BB algorithm, the BBQ variant focuses on the local minima and maxima in the sample path of an economic time series y_t . The definition remains unaltered; a local peak (trough) occurs at time t whenever $\{y_t > (<)y_{t \pm k}\}$, with $k = 1, \dots, K$. In addition, and since we refer to quarterly data, k is set equal to 2, to ensure that a local maximum or minimum is found at t relative to the two quarters on either side, so that

$$\text{peak at } t = \{(y_{t-2}, y_{t-1}) < y_t > (y_{t+1}, y_{t+2})\} \quad (3)$$

$$\text{trough at } t = \{(y_{t-2}, y_{t-1}) > y_t < (y_{t+1}, y_{t+2})\}. \quad (4)$$

The censoring procedures are maintained and the corresponding rules are adjusted to the respective ones followed by the BB algorithm, through the specification of the minimal length of cycles and phases in terms of quarters. The imposition of turning points' censoring is necessary to ensure the alternation of peaks and troughs, a minimum duration of two quarters for each business cycle phase and a minimum of five quarters for each complete business cycle.²²

(d) Aggregation of turning points in individual series

In order to exploit business cycle information contained in individual monthly economic series picturing important sectors and activities in the Greek economy, we apply the non-parametric automated algorithm following Harding and Pagan (2006b) (H&P). In a two-step procedure, the specific cycle turns are first identified in the selected individual series and the individually derived switch points are then “aggregated” to provide a business cycle chronology.²³

More specifically, specific turning points and cycles in the individual economic series are first identified using the BB algorithm for monthly series. Given the derived specific cycles, the aggregated cycle is established on the basis of calculated and median distances to peaks and troughs, clusters and central dates of clusters of peaks and troughs, and distances from the centre of clusters.²⁴ Once again, several censoring rules are implemented in order to impose alternation between peaks and troughs and restrictions on the minimum phase and cycle durations, in order to preserve the basic features of the NBER criteria.

(e) Markov switching model

Finally, in a specification according to Hamilton (1989), we model the business cycle as a two-state Markov switching process. The growth rate of the selected measure of economic activity²⁵ Δy_t is represented by

$$\Delta y_t = \mu(S_t) + \sum_{i=1}^q \varphi_i (\Delta y_{t-i} - \mu(S_{t-i})) + \varepsilon_t, \quad (5)$$

$$\varepsilon_t \sim \text{i.i.d.} N(0, \sigma^2), \quad (6)$$

where, the mean growth rate of economic activity μ depends on the state variable $S_t = \{0, 1\}$ and switches between two regimes, with $\mu(S_t) = \mu_0(1 - S_t) + \mu_1 S_t$ depending on economic activity switching between expansions and contractions. The disturbance term is assumed to be state-independent and φ_i describe the autoregressive parameters. Since we are dealing with the classical concept of business cycles, the imposition of two states is intuitively appealing. The transition probabilities for the potential switches from the one business cycle regime to the other are given by $\Pr(S_t = i | S_{t-1} = j) = P_{ij}$, and hence, the probability process driving the state variable is captured by four transition probabilities such as $p = \Pr[S_t = 1 | S_{t-1} = 1]$, $1 - p = \Pr[S_t = 0 | S_{t-1} = 1]$, $q = \Pr[S_t = 0 | S_{t-1} = 0]$ and $1 - q = \Pr[S_t = 1 | S_{t-1} = 0]$.

In order to derive a business cycle chronology on the basis of the results from the Markov switching model, we need to convert the transition probabilities into turning point dates. For that reason we adopt the simple rule that a period of recession is defined as a period in time where the inferred probability of recession is greater than 0.5.²⁷

3.3. Measuring business cycle features

Provided that the obtained chronologies are characterised by consistency and coherence and can be used to establish a business cycle reference chronology for Greek economic activity, the identified turning point dates are used to examine specific business cycle features. Such features usually refer to cycle phases or complete cycles and are investigated using the derived switch points alone or the turning points in conjunction with the underlying series. In the present reference to features of the Greek business cycle, we focus on the measurement of cycle and phase durations as well as amplitudes, and also the measurement of cumulative movements and excess cumulative movements within phases. The evidence provided by these measures reflects information on the features of the length, depth and shape of business cycles and phases.

The duration measures as well as their averages and standard deviations, which directly result from the derived turning points, offer comparative information on full cycle and phase lengths for the time period under investigation. The measurement of phase

amplitudes, cumulative movements and excess cumulative movements, which requires taking into account the underlying data series, leads to evidence on the depth and shape of Greek business cycles and phases for a time period of over 40 years. These measurements are based on the triangle approximation approach.²⁸

4. Results

The five dating procedures as outlined in Section 3 are applied to Greek data for the time period January 1970 (1970Q1)-December 2012 (2012Q4). They lead to five distinct chronologies for the Greek business cycle and the corresponding exact peak and trough dates (months or quarters) are presented in Table 1. In addition, Figure C2 pictures the smoothed recession probabilities resulting from the application of the MS model. On the basis of the obtained individual chronologies, we derive the reference chronology for the Greek business cycle and the time period under investigation. This allows reference to specific Greek business cycle characteristics.

4.1. Greek business cycle reference chronology

Careful observation of the obtained switch points makes evident that the derived chronologies exhibit a significant degree of consistency, since in most cases the applications suggest very similar, and in some cases, identical dates for business cycle peaks and troughs. Still, there are a few registered deviations which lead to discrepancies in both the timing and length of the suggested phases and cycles which certainly deserve comment. Both similarities and differences should be assessed within the framework of the evaluation of the underlying distinct algorithms.

First, with regard to the recorded coherence, the related results suggest that there is general agreement as to the timing of economic recessions and expansions in Greece for the time period starting in January 1970 (1970Q1) and ending in December 2012 (2012Q4). This does not come as a surprise, since historically the detected cycles in Greek economic activity follow, and reflect quite concrete domestic and international occurrences, and developments. Even though the different methodologies applied vary in terms of many of their underlying characteristics, the evidence on the derived peak and trough dates implies that variation in the dating methodology does not lead to significant variation in the identified historical stylised facts of the Greek business cycle.

Second, with reference to the identified divergences in dating the Greek business cycle, on the basis of the provided results, we can differentiate between differences which mostly appear to be related to specific subjective choices and those which are to a greater degree related to the applied method.

A more detailed analysis of the exact derived switch points helps to understand the general concepts, underlined previously, and contributes to the overall assessment of the choice to conduct a comparative exercise, as well as the evaluation of the applied procedures and the derived results. According to Table 1, in four out of five (with the exception of the BBQ algorithm) cases the algorithms identify six full, even though not identical, peak-to-peak cycles. The identification of the last peak-to-peak cycle confirms in all cases the beginning of a period of recession for the Greek economy, starting in 2008. At the same time, it is observed that the last registered peak date is not followed by a trough date, and hence the last trough-to-trough cycle and the last peak-to-trough phase remain incomplete. This indicates that, until the end of the time period under investigation,

Table 1. **Derived business cycle chronologies for Greek economic activity**
January 1970 (1970Q1)-December 2012 (2012Q4)

GDP growth rule quarterly GDP		BB interpolated monthly GDP		BBQ quarterly GDP		H&P algorithm monthly Series		MS model quarterly GDP	
Peak	Trough	Peak	Trough	Peak	Trough	Peak	Trough	Peak	Trough
1973Q4	1974Q3	1973M10	1974M7	1973Q4	1974Q3	1973M11	1974M9	1973Q3	1974Q3
1980Q1	1981Q2	1980M3	1981M6	1980Q1	1983Q2	1979M12	1981M2	1980Q1	1981Q1
1981Q4	1983Q2	1981M11	1983M5			1982M3	1983M4	1981Q4	1983Q1
1986Q2	1987Q2	1985M10	1987M1	1985Q4	1987Q2	1985M11	1987M5	1985Q4	1987Q2
		1990M1	1990M9	1990Q1	1991Q2	1990M1	1992M12	1989Q4	1990Q3
1992Q1	1993Q1	1991M11	1992M11	1992Q1	1993Q1			1992Q1	1993Q1
1994Q3	1995Q2								
						2000M5	2001M10		
2008Q1		2008M4		2008Q1		2008M3		2008Q1	

namely the end of 2012, Greek economic activity has not exited the most recent recessionary regime. It is no coincidence that the latter holds independently of the dating procedure applied.

In examining the exact timing of the located individual business cycles and phases, which the Greek economy is suggested to have experienced during the past four decades, interesting information emerges with regard to historical stylised facts. The accuracy of the obtained dates and their coherence is validated by the fact that the referred facts are, in most cases, in agreement with both the European and broader international experience.²⁹ More specifically, all procedures without exception lead to the identification of the mid-1970s recession, which is associated with the first oil price shock. The identification of the 1973 peak and the 1974 trough quarters is characterised by general agreement among the methodologies, with one exception given by the MS model. The apparent short duration of the specific recession for Greece is in accord with other findings in the respective literature, as outlined, for example, by Biscarri (2002), who states that the Greek economy was the first, compared to the other European countries under investigation, to recover from the crisis.³⁰

Due to the resulting discrepancies, the located switch points during the early 1980s and the early 1990s as well raise some doubts as to the exact evolution of the Greek business cycle. In both cases, the main issue concerns the question whether the Greek economy experienced a long-lasting single recession, or two distinct short-lived recessions, also known as a “double-dip” recessions. As such, it is not disputed whether the Greek economy experienced significant fluctuations in economic activity in the early 1980s and 1990s, but merely whether they have been interrupted by short periods of recovery or not.

More specifically, in the case of the 1980s, the evidence suggests either two short-lived recessions between approximately 1980-81 and 1982-83, or one long-lasting single recession, from early 1980 to mid-1983. The case for a double early 1980s recession does not seem implausible and is further enforced by the fact that it can be connected to the second oil price shock.³¹ Furthermore, it corresponds with the double-dip recession, which is identified in the related literature for other European countries (see for example, Biscarri, 2002³²). Similar findings by Bruno and Otranto (2004) for Italy lead to the identification of either a single long early 1980s recession or two distinct recessions separated by a short recovery in the second half of 1981, depending on the procedure applied. Along the same line of argumentation, and on the basis of the corresponding findings, a double early 1990s

recession appears plausible, even though some procedures identify a single one. Note that Biscarri (2002) identifies one long single early 1990s recession for Greece lasting three and a half years. Again, Bruno and Otranto (2004) provide, as to the early 1990s recession in Italy, indications for both a single longer period recession from 1990 to 1993 and for a short recession in 1990, followed by another one over the period 1992-93.

The ascertained consistency among the derived dates with reference to the 1986-87 contraction is clearly related to the relevant domestic developments with reference to the restrictive economic policy and adjustment measures taken by that time in Greece. In contrast, the confirmation of the identified 1994-95 recession (by the GDP growth rule) and the early 2000s recessionary period (by the H&P algorithm) remains doubtful. With reference to a potential early 2000s, Biscarri (2002) argues that there is evidence on a deceleration of economic activity in Greece in the early 2000s, something that appears to hold for other European countries as well. However, Biscarri stresses that it is ambiguous whether this incident qualifies as an “official” recession.

More importantly, and as already indicated in the beginning of this section, all applied procedures clearly identify the beginning of the late 2000s recession for the Greek economy, which is identified in almost all cases in the second quarter of 2008 (the exception being the BB method). It follows that the derived exact peak date and, hence, the exact point in time of the end of the last period of expansion for the Greek economy is mostly located within the first quarter of 2008. At the same time, the obtained results do not provide, on the basis of data available up to December 2012, any evidence on a trough date following the last peak date recorded in the beginning 2008, implying the continuation of the recessionary regime throughout 2012. This assertion is also confirmed by the smoothed recession probabilities resulting from the application of the MS model which continue to be very high until the end of 2012. Still, it is worth noticing that the respective probabilities recorded two consecutive decreases in the third and fourth quarter of 2012, even though they remained above 0.9 (see Figure C2).

Overall, the consistency that characterises the switch point dates obtained by different dating methodologies facilitates and allows the suggestion of a quarterly reference chronology for the Greek business cycle over a time period from the first quarter of 1970 to the fourth quarter of 2012. To do that, we first rely on the dates provided by the methodologies which mostly agree on the inferred peak and trough points. In cases of disagreements, we take into account and evaluate specific characteristics of the applied algorithms.

Basic agreement leads to identification of the turning points related to the 1973-74 and 1985-87 periods, as well as the beginning of the most recent recession in the late 2000s. The single lasting or double-dip early 1980s and 1990s question is solved by taking advantage of the methodological characteristics of both the non-parametric and parametric procedures used, in which the implied rules are formulated to satisfy the requirements for the basic business cycle characteristics. At the same time, however, the potential role of subjective choices and censoring rules incorporated in the BB procedures is considered. In addition, the H&P algorithm provides the supplementary benefit of relying on data other than the GDP series. The same holds for the derivation of the monthly GDP series, which is used to apply the BB procedure, something that renders this procedure particularly attractive since it also combines information included in quarterly GDP and individual monthly series.

It is indicative that only the H&P algorithm locates a recessionary period starting in 2000 and ending in 2001, while the BB procedure does not. This can be explained by the fact that both include information contained in the underlying monthly data series, potentially reflecting international developments and their impact on the domestic environment (for example, through the path of imports and industrial production). However, the H&P algorithm relies solely on that information, whereas the monthly BB procedure combines this kind of information with that provided by the measure of aggregate economic activity in Greece, not actually justifying the identification of a recessionary period for the Greek economy in the early 2000s. Moreover, the sensitivity of the simple GDP growth rule to data revisions and data transformations, such as seasonal adjustment, does not favour the acceptance of dates which are not confirmed by any of the other procedures applied. Finally, beside mostly robust peak and trough dates offered by the MS model, which does not rely on any subjective choices, the evolution of the derived recession probabilities constitutes essential additional evidence which can potentially be used to interpret early signals for upcoming turns in economic activity.

As a result, the reference chronology can be derived as a product of the combination of the advantages provided by all the applied algorithms, whereby the datings provided by the application of the monthly BB and the MS algorithms seem to better qualify as benchmarks. The suggested reference chronology, which offers the exact turning points and is presented in Table 2, can be said to accurately present a robust chronology for the Greek business cycle over the time period 1970Q1 to 2012Q4. The quarterly GDP data series together with the identified recessions, which are represented by shaded areas, are pictured in Figure C1.

Table 2. Suggested business cycle reference chronology for the Greek economy, 1970Q1 - 2012Q4

Business cycle reference chronology, quarterly

Peak	Trough
1973Q4	1974Q3
1980Q1	1981Q1
1981Q4	1983Q2
1985Q4	1987Q2
1990Q1	1990Q3
1992Q1	1993Q1
2008Q1	

4.2. Greek business cycle features

The establishment of a robust reference cycle chronology for Greek economic activity and, hence, the exact turning point dates for the Greek business cycle can be used for inference to specific cycle and phases' characteristics. These are offered in Table 3,³³ which presents evidence on durations, amplitudes, cumulated movements and excess cumulated movements. Note that no quantitative inference can be made to the corresponding last trough-to-trough full cycle and contractionary phase, since they will both remain incomplete until the end of the most recent recession and the identification of the corresponding turning point.

With reference to durations, or the length, of the detected full cycles and the related phases, we consider full cycles both as cycles from one peak to the next (P to P) and from

one trough to the next (T to T) and phases by distinguishing between expansions and contractions. We also provide the corresponding mean durations and standard deviations. Not surprisingly, the most striking characteristic pertains to the deviation in duration between expansions and contractions. The mean duration of expansions amounts to 18.7 quarters, while contractionary regimes in Greece last 4.2 quarters on average. This is in accordance with the internationally well established business cycle characteristic of asymmetry between expansions and contractions. The specific feature is reflected in significantly longer durations of expansionary regimes than contractionary ones. It should be stressed that this specific characteristic is not expected to change even after the completion of the most recent recession.³⁴

The calculated durations also lead to well distinguished standard deviation measures, with a value of 21.3 for expansions and 1.6 for contractions. The duration measures further indicate that the longest expansion lasted 60 quarters and is the one that was interrupted in the year 2008 by the beginning of the most recent contraction. The longest recessions lasted 6 quarters, without taking into account the last one, which according to the above dating had already recorded a duration of 19 quarters until the end of 2012.

With reference to full cycles, the last one recorded is identified as the longest peak-to-peak full cycle, with a duration of 64 quarters. A particularly long trough-to-trough cycle is expected to be registered after the completion of the most recent recessionary phase and will include the longest expansionary and contractionary phases, within the investigated time period.

Table 3. Durations, amplitudes, cumulated movements and excess cumulated movements of the identified cycles and/or phases

1970Q1-2012Q4

Durations				Amplitudes (%)		Cumulated movements (%)		Excess cumulated movements (%)	
Full BC durations		Phase durations		Phase amplitudes		Within phases		Within phases	
P-P	T-T	Exp.	Contr.	Exp.	Contr.	Exp.	Contr.	Exp.	Contr.
25	26	22	3	35.8	-14.2	495.2	-23.7	-21.1	22.1
7	9	3	4	4.5	-5.5	2.8	-18.2	91.3	-41.7
16	16	10	6	12.4	-8.8	55.8	-34.0	20.3	-12.7
17	13	11	6	13.1	-9.0	84.5	-34.8	-8.1	-11.9
8	10	6	2	12.3	-9.9	61.6	-12.7	-51.0	21.5
64		60	4	49.9	-4.8	1431.0	-11.6	6.0	4.2
<i>M</i> 22.8	14.8	18.7	4.2	21.3	-8.7	355.2	-22.5	6.3	-3.1
<i>SD</i> 21.2	6.8	21.3	1.6	-	-	-	-	-	-

Note: Phase information is provided only for completed phases. P-P = peak to peak; T-T = trough to trough; Exp. = expansionary; Contr. = contractionary. Average values and standard deviations are given in the last rows. The excess cumulated movements are presented here in relation to the triangle.

In terms of phase amplitudes, or the depth of the recorded cycle phases, the highest contraction amplitude amounts to -14.2% and refers to the 1973-74 recessionary period (without again taking into account the most recent, since not yet completed, recessionary phase of the Greek business cycle), while the highest expansion amplitude is recorded during the last and longest expansion and reaches a level of 49.9%. Asymmetry between expansions and contractions is once again featured, by an average expansion amplitude of 21.3% and average contraction amplitude of -8.7%. Information on the shape of the

identified business cycle phases is provided by cumulated movements and excess cumulated movements, which imply that during expansions there have been considerable cumulated gains in output, when compared to the level before the turning point. The cumulated losses recorded for contractions are considerably lower, even though still not negligible. At the same time, the evidence provided by the calculated excess cumulated movements appears to be mixed. More specifically, in three out of the six cases of expansions, the significant positive (negative) excess measures suggest that the actual cumulative movements, and hence the actual gain, are lower (larger) than measured by the triangular approximation. As for contractions, in three out of the six cases the negative excess measures suggest that there is a much larger loss in output during recessions than measured by the triangular representation, indicating more rapid decline in growth when coming out of expansion.

Overall, it appears that a distinct role with reference to the basic characteristics of the Greek business cycle can be attributed to the last two cycle phases: the last and longest expansionary period which lasted about 15 years and the last, not yet completed, contractionary period already lasting about five years. In other words, this could be seen to imply that the underlying period of investigation and, hence, the referred cycles and their characteristics can be separated into two distinct periods: a period of more frequent alternations between longer expansionary and shorter recessionary regimes (lasting from 1970 to 1993); and, a period of an exceptionally (as compared to previous ones) long expansionary and an exceptionally long (as compared to previous ones) recessionary regime. This is something that is well reflected in the evidence obtained by both the BB algorithm and the MS model. In that case, the acceptance of the assertion that the underlying structure of the Greek business cycle has changed or is adjusting over time would imply that both the last and longest expansion and, in particular, the latest and longest (even though not completed) recession have been driven by different factors than the previous ones. This certainly appears to be the case with reference to the latest contraction, which has been evidently related to the international developments in the late 2000s, but was mainly driven by deeply rooted domestic weaknesses and imbalances which were brought to the surface. Since the confrontation of the latter requires long-term adjustments and severe interventions usually taking time to become effective, we would tend to expect that the basic characteristics of the underlying full cycle and phase, such as length and depth, would accordingly adjust. Finally and against the background of adjusting business cycle structure, it becomes questionable whether past experience on the shape of the expansionary phases could or should be used to form assumptions on a potential rapid or slow recovery in the early phase of the expansion period, which is expected to follow the most recent contractionary period.

5. Conclusions

The purpose of the present work is to establish a reference chronology for the Greek business cycle and the time period beginning in early 1970 and ending in late 2012. Within this framework, we search for evidence on the Greek economy entering the most recent recessionary regime in the late 2000s and confirmation for the continuation of the contraction until the end of 2012. To do that, we apply five different business cycle dating procedures in a comparative exercise, in order to take advantage of the information offered by the distinct algorithms, while controlling for the consistency of the obtained turning

points. To derive a reference chronology for aggregate Greek economic activity we use quarterly GDP data and also take into account information included in individual monthly economic series.

The analysis of the provided evidence clearly favours the performance of the comparative exercise. On the one hand, the basically consistent evidence and coherence among the located peak and trough dates provided by the GDP growth rule, the BB, the BBQ, the H&P automated dating algorithms and the MS model, clearly favours the derivation of a reference chronology. On the other hand and in cases of discrepancies, the evidence which qualifies as a benchmark provided by robust procedures, such as the BB algorithm and the M&S model, is used to decide on the identification of the related turning points. The obtained reference chronology is considered to describe the exact switch dates for the Greek business cycle and the time period 1970Q1 to 2012Q4.

The located turning points identify the mid-1970s recession, the early 1980s “double” recession, the mid-1980s recession and the early 1990s “double” recession. In addition to the identification of historically well-established complete cycles and cycle phases, the derived chronology clearly confirms the beginning of a recessionary period for Greek aggregate economic activity in the late 2000s. The first quarter of 2008 is dated as the peak quarter and indicates the end of the more recent expansionary regime which lasted 60 quarters. It follows that the second quarter of 2008 presents the first quarter of the most recent recessionary regime for the Greek economy. The lack of evidence on a trough date that would signal the exit from the recession confirms that the recessionary phase continued at least up to the end of 2012. This evidence makes more than clear the role played by the interrelations and interdependencies across countries and country groups, but also the significance of the domestic fundamentals in shaping the business cycle of the Greek economy.

In addition, the finding that widely accepted business cycle stylised facts, such as the significant asymmetry characteristic between expansions and recessions, hold for the Greek business cycle as well supports the argument of the robustness of the derived reference chronology. More specifically, the evidence suggests that durations as well as amplitudes indicate different behavior during expansions than during contractions. This holds independently of the fact that the underlying structure of the Greek business cycle might be considered to have changed since the early 1990s.

The derivation of a reliable reference chronology can, moreover, form the base for further research on Greek business cycles. Related research may refer to detecting turning points in real-time and forecasting turning points, or investigating the issue of business cycle synchronisation, but may also involve exercises such as the construction of coincident and/or leading indicators. Such research can very well facilitate the better understanding and monitoring of the current and future state of economic activity in Greece, which in turn can be proven to be particularly helpful for institutions, enterprises but also public authorities.

Notes

1. For a related dating application, which however relies solely on the non-parametric BB and BBQ algorithms, see Tsouma (2011).
2. The applied rule is related to the popular “two-quarters” (two quarters of negative growth signalling the termination of an expansion) rule of thumb, which is, even though of an unclear

origin, sometimes attributed (as Harding and Pagan (2003a, p. 22) indicate) to Arthur Okun (see, for example Harding, 1997). Others (for example, Layton and Banerji, 2003) attribute this rule to Shiskin.

3. See Layton and Banerji (2003) for the conceptualisation of the cycle and also a more recent discussion on the use of GDP for business cycle dating.
4. Examples of applications applying simple rules are provided in Birchenhall et al. (2001), for the case of the UK, Harding (1997) for an application to the Australian coincident index and Mylonidis (2003), who uses several criteria to obtain a recession chronology for Greek economic activity.
5. The author uses a modified version as operationalised by Artis et al. (1997).
6. The authors apply the BB procedure, augmented with an amplitude/phase-length criterion, on the basis of different monthly GDP series for the euro area.
7. A non-parametric algorithm (on the basis of the theory of Markov chains) related to the BB dating rule is applied by Artis et al. (2003) for the euro area and the main euro area countries (see also Artis et al., 2004c). In a similar application, Artis et al. (2004b) characterise the business cycle for EMU accession countries. A dating algorithm is developed, also on the basis of a Markov chain, by Proietti (2005) for an application to Italy and the USA.
8. The authors investigate the real-time performance of a Markov-switching model with the aim to replicate the NBER business cycle chronology and to stress the timing advantage. The latter can be very notable, especially with reference to dating business cycle troughs.
9. In Golosnoy and Hogrefe (2009), the results from the DFMS approach are compared to the proposed novel sequential approach for providing timely signals about changes of the US business cycle phase.
10. In his review, the author concludes as a whole that none of the procedures are clearly superior and argues for the view of complementarity of procedures in building a consensus.
11. See the related debate with Hamilton, based on the authors' results, as expressed in the comment by Hamilton (2003) and the rejoinder by Harding and Pagan (2003).
12. The author applies three regime switching models and provides, within this context, an explicit turning point chronology for Greece.
13. In this work, we choose the concept of the classical business cycle in order to focus on recessions rather than on growth retardations and retain the basic elements inherent in the Burns and Mitchell (1947) business cycle definition and the procedures followed by the NBER business cycle Dating Committee.
14. The use of GDP data is in accordance with the argument by Burns and Mitchell that GDP measures would be appropriate for reflecting and measuring aggregate economic activity (Burns and Mitchell, 1947, p. 72).
15. Note that the selection of individual series is to a significant degree dictated by historical data availability restrictions.
16. We believe that the specific rule applies better to Greek GDP data than the "two-quarters" rule (which identifies too many recessions) and is also preferred over a cutoff or threshold rule.
17. See Bry and Boschan (1971), pp. 2-3. Table A1 in Annex A describes the basic steps of the procedure.
18. The basic GAUSS code for the implementation of the BB business cycle dating algorithm is taken from www.princeton.edu/~Emwatson/publi.html. The applied procedure for turning points location as implemented by Watson consists of different steps, in accordance with the description provided in Annex A.
19. Harding (2003, p. 3-4) indicates that the most important reason for censoring turning points is to enhance the effect of nonlinearities. In the case of nonlinearities, large changes are expected to differ significantly from small changes and nonlinearity is expected to show up in the path taken between successive turning points. In that sense, censoring is implemented in order to ensure that phases are sufficiently long so as to make any nonlinearity evident.
20. The application corresponds to case two in Chow and Lin (1971, pp. 374-375) as regards the assumption for the residuals (Robertson and Tallman, 1999). On applications and testing of the Chow-Lin but also other interpolation or disaggregation approaches, see Mönch and Uhlig (2005), Billio, Caporin and Cazzavillan (2007), Layton and Banerji (2003), Artis (2002) and Miralles et al. (2003).

21. A GAUSS version of James Engel's business cycle dating programs is provided at www.ncer.edu.au/data.
22. In the present application to the Greek business cycle, the censoring rules are adjusted so that phases and cycles are eliminated with duration less than 3 and 6 quarters, respectively.
23. In opposing this algorithm to procedures where business cycle turning points are established on the basis of constructed coincident indicators, it is sometimes termed "indirect", as opposed to direct ones (see Bruno and Otranto, 2004). I thank Professor Don Harding for kindly providing the corresponding GAUSS code for the implementation of the specific algorithm.
24. See Annex B, part B1 for more details.
25. We take log differences.
26. We select four autoregressive terms.
27. The basic GAUSS code for the implementation of the Markov switching model is taken from <http://weber.ucsd.edu/%7Ejhamilton/software.htm#Markov> and is part of the data and software from James D. Hamilton. On the basis of the MS model, we calculate both filtered and smoothed recession probabilities.
28. See Annex B, part B2 for more details and related references.
29. Note the approximate agreement with recessionary regimes identified in the literature for the EU and the euro area countries. See for example, Billio et al. (2007), Anas et al. (2007) and Chen (2007).
30. The mid-1970s recession is a recession identified for a great number of countries worldwide and is always related to the 1974 oil price rises. Still, as indicated by Artis et al. (1997), it is observed that in some countries the peaks predated these increases.
31. Note that in the present application, the respective findings may be related to the short duration of potential cycle phases which remain unidentified due to the involved censoring rules.
32. Note that according to Biscarri (2002), and in contrast to our findings, Greece escaped the early 1980s recession and regained the synchronicity with the other European countries during the recovery from the recession of the 1990s.
33. For reasons of comparison, Table C1 provides similar information on the durations of full cycles and phases for the distinct chronologies derived by application of the different methodologies. In all cases the provided evidence agrees with the information extracted on the basis of the reference chronology.
34. This will of course hold under the assumption that the current recessionary regime will end sometime within the upcoming years.

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ANNEX A

Table A1. Procedure for programmed determination of turning points

1. Determination of extremes and substitution of values.
2. Determination of cycles in 12-month moving average (extremes replaced).
A. Identification of points higher (or lower) than 5 months on either side.
B. Enforcement of alternation of turns by selecting highest of multiple peaks (or lowest of multiple troughs).
3. Determination of corresponding turns in Spencer curve (extremes replaced).
A. Identification of highest (or lowest) value within ± 5 months of selected turn in 12-month moving average.
B. Enforcement of minimum cycle duration of 15 months by eliminating lower peaks and higher troughs of shorter cycles.
4. Determination of corresponding turns in short-term moving average of 3 to 6 months, depending on MCD (months of cyclical dominance).
A. Identification of highest (or lowest) value within ± 5 months of selected turn in Spencer curve.
5. Determination of turning points in unsmoothed series.
A. Identification of highest (or lowest) value within ± 4 months, or MCD term, whichever is larger, of selected turn in short-term moving average.
B. Elimination of turns within 6 months of beginning and end of series.
C. Elimination of peaks (or troughs) at both ends of series which are lower (or higher) than values closer to end.
D. Elimination of cycles whose duration is less than 15 months.
E. Elimination of phases whose duration is less than 5 months.
6. Statement of final turning points.

Source: Bry and Boschan (1971), p. 21.

ANNEX B

B1. Notes on aggregation of specific cycle turning points in individual series

Following Harding and Pagan (2006b), specific cycle turns are identified using the individual economic series and are then aggregated to provide the business cycle chronology. Let t_i^P and t_i^T be the vectors containing the dates to peaks and troughs, respectively, in the i th specific cycle. Functions $\tau_i^P(t)$ and $\tau_i^T(t)$ are then defined, measuring the distance in months from data t to the nearest peaks and troughs, respectively, in the i th specific cycle, while functions $\tau^P(t)$ and $\tau^T(t)$ measure the median distance from t to the set of nearest peaks and troughs, respectively. The local minima in these functions give the *central dates of clusters of peaks* comprising dates at which the distance in months to the sets of nearest peaks and troughs are minimised. The vectors of dates of local minima in $\tau^P(t)$ and $\tau^T(t)$ are given by M^P and M^T , respectively. In other words, these are the vectors containing the dates of the clusters of peaks and troughs. Finally, it is controlled whether or not the peak (trough) nearest to the centre of that cluster is in that cluster, which is provided by the conditions that it is not nearer to the centre of another cluster and it is less than a distance $\bar{d}$ from the centre of the cluster. If m_j^P and m_j^T are the j th elements of M^P and M^T , then $C(m_j^P)$ and $C(m_j^T)$ represent the clusters of peaks and troughs centred on m_j^P and m_j^T , respectively.¹

B2. Notes on measuring selected business cycle features

The obtained reference chronology as well as the underlying quarterly GDP series are used to measure specific features of the Greek business cycle. Let D_i represent the duration of the i th phase, whether expansion or recession. Defined by two consecutive turning points (trough-to-peak or peak-to-trough) that fall in periods t and $t+d$, this returns $D_i = d$. The duration of a complete cycle can then be easily measured by the addition of the durations of two consecutive phases. Now, if the underlying data series is denoted by Y_t , the amplitude or depth of the i th phase, A_i , is measured as $A_i = y_{t+d} - y_t = \Delta_d y_{t+d}$, where $y_t = \ln(Y_t)$.² Here, the log has the natural interpretation of the approximate percentage change between trough (peak) and peak (trough) (see Harding and Pagan, 2006b, p. 6).

Following Harding and Pagan (2002, 2006), Krolzig and Toro (2005) and Camacho et al. (2008), we combine the measures of phase duration and amplitude and consider a cycle phase as a triangle. The base of the triangle is considered to be the duration of the business cycle phase, the height stands for the amplitude, and the hypotenuse is assumed to describe the path of the underlying series for the hypothetical case of a linear transition from one turning points to the next. It follows that, the triangle area presents an intuitive

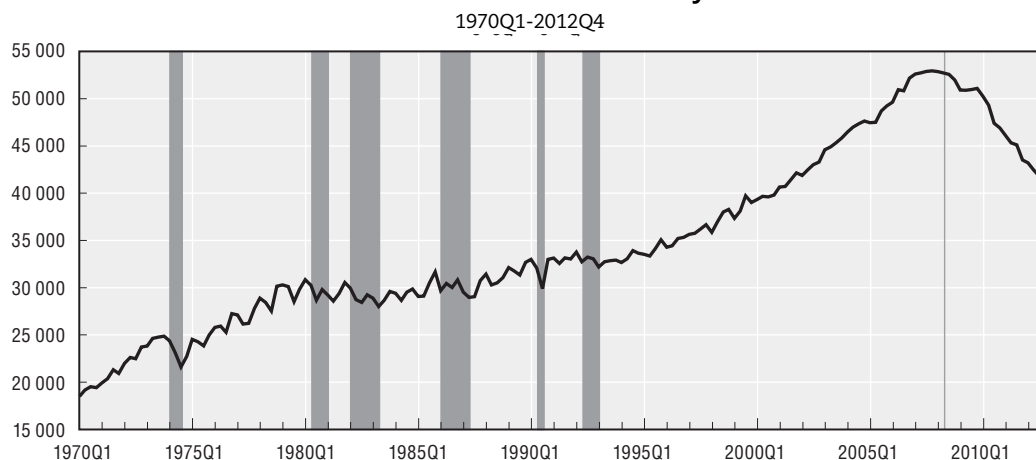
approximation for the cumulated gain (loss) in output between successive turning points, while it allows, at the same time, the examination of the concavity or convexity, and, hence, shape of the cycle phase. Let then the product $C_{Ti} = 0.5(D_i * A_i)$ describe the “triangle approximation” to the cumulated movements. However, since the actual cumulative movements C_i may in practice differ from C_{Ti} , we need to calculate the corresponding deviation. This is given by the measure of the “excess cumulated movements” E_i , where $E_i = (C_{Ti} - C_i + 0.5 * A_i)$. In interpreting the resulting difference, we note that negative (positive) excess measures indicate that the actual cumulative movements, gains or losses, are larger (smaller) than the triangular approximation for expansions and contractions, respectively. The respective excess measure may, at the same time, be used to comment on the abruptness with which the series enters in and exits from a phase. Within this context, great positive (negative) divergences from a triangle in the expansion phase reflect rapid (slow) recovery in the early stage of an expansion; accordingly, great negative (positive) divergences from a triangle in the contraction phase indicate rapid (slow) decline in the early stage of the contraction.³

Notes

1. As indicated by Harding and Pagan (2006b), if local minima are not unique, it may be necessary to break ties, in order to decide on the turning point, which is done through the algorithm by looking at higher percentiles than the median until a unique local minimum is found.
2. In assuming that Y_t is positive for all t , we can work with $y_t = \ln Y_t$, since this transformation, being monotonic, will not impact on the determination of turning points (see Harding and Pagan, 2003, p. 2).
3. Note that, in this context, “positive” and “negative” divergences indicate greater gains and greater losses, which according to the definition of E_i given above are signaled by a negative sign for expansions and contractions, respectively.

ANNEX C

Figure C1. **Quarterly GDP and suggested reference business cycle chronology for Greek economic activity**



Note: GDP, in million euro, is plotted at constant (2005 = 100) prices and is seasonally adjusted. Shaded areas describe the identified recession phases, while the line at 2008Q2 presents the beginning of the latest recession.

Figure C2. **Smoothed probabilities of recession from MS model**

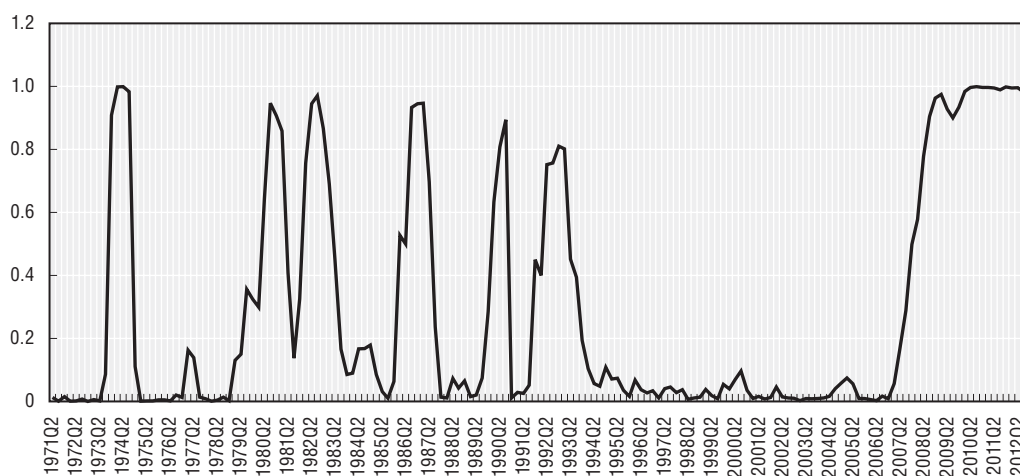


Table C1. Durations of identified Greek business cycles

January 1970 (1970Q1)-December 2012 (2012Q4)

GDP growth rule quarterly GDP				BB Interpolated monthly GDP				BBQ quarterly GDP				H&P algorithm monthly Series				MS model quarterly GDP			
Full BC durations (quarters)		Phase durations (quarters)		Full BC durations (months)		Phase durations (months)		Full BC durations (quarters)		Phase durations (quarters)		Full BC durations (months)		Phase durations (months)		Full BC durations (quarters)		Phase durations (quarters)	
P-P	T-T	E	C	P-P	T-T	E	C	P-P	T-T	E	C	P-P	T-T	E	C	P-P	T-T	E	C
25	27	22	3	77	83	68	9	25	35	22	3	73	77	63	10	26	26	22	4
7	8	2	5	20	23	5	15	23	16	10	13	27	26	13	14	7	8	3	4
18	16	12	6	47	44	29	18	17	16	11	6	44	47	31	13	16	17	11	5
23	23	19	4	51	44	36	15	8	7	3	5	50	67	32	18	16	13	10	6
10	9	6	4	22	26	14	8	64		60	4	124	106	89	35	9	10	6	3
54		51	3	197		185	12					94		77	17	64		60	4
M 22.8	16.6	18.7	4.2	69.0	44.0	56.2	12.8	27.4	18.5	21.2	6.2	68.7	64.6	50.8	17.8	23.0	14.8	18.7	4.3
SD 16.8	8.4	17.5	1.2	66.1	23.9	66.8	3.9	21.5	11.8	22.7	4.0	35.8	30.3	29.9	8.9	21.2	7.1	21.3	1.0

Note: Phase and cycle information is provided only for completed phases and cycles. P-P = peak to peak; T-T = trough to trough; E = expansionary; C = contractionary. Average values and standard deviations (in months or quarters) are given in the last row.

Identifying leading indicators of real activity and inflation for Turkey, 1988-2010: A pseudo out-of-sample forecasting approach

by
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This paper develops a set of leading indicators for industrial production growth and changes in consumer price inflation by accounting for changes in the policy regime that have occurred for the Turkish economy over the sample period 1988-2010. The choice of indicators is based on a pseudo out-of-sample forecasting exercise that is implemented by Leigh and Rossi (2002), and Stock and Watson (2003), amongst others. Our findings provide evidence on the factors determining changes in real activity and inflation over an extended sample period that encompasses episodes of volatile inflation and output growth as well as the recent experience of disinflation and normalisation for the Turkish economy.

Keywords: Real activity, inflation, leading indicators, out-of-sample forecasting, combination forecasts, inflation targeting, Turkey.

JEL classification: E1, E32, E37, E58, F43, O52

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1. Introduction

In this paper, we develop a set of leading indicators to predict changes in real activity and inflation at the monthly level for Turkey. Our study builds on the analysis of Leigh and Rossi (2002) who examine the forecasting performance of 42 candidate indicators for output growth and inflation over the period 1986-2002 in Turkey. However, unlike their analysis, we examine the efficacy of a large set of variables for forecasting industrial production growth and inflation changes by accounting for changes in the policy regime that have occurred in Turkey over the extended sample period 1988-2010.

Following the approach in Leigh and Rossi (2002), and Stock and Watson (2003), we use pseudo out-of-sample forecasting techniques to examine the efficacy of up to 51 real and financial candidate indicators for forecasting industrial production growth and changes in inflation over the period 1988-2010. To account for the alternative policy regimes in effect, we consider three sub-samples of our sample period, namely, the sub-samples comprising 1988-2000, 1996-2005 and 2001-10, respectively. The first sub-sample of 1988-2000 is characterised by the 1994 financial crisis and the volatile inflation and output growth of the 1990s. The second sub-sample 1996-2005 is motivated by the run-up to the crisis of 2000-01 together with the crisis itself and its immediate aftermath, when Turkey transited from a managed floating exchange rate regime to floating exchange rates. Following the crisis of 2000-01, Turkey also implemented a wide set of reforms as part of an IMF-sponsored stabilisation plan, including banking and financial sector reform, a move to central bank independence, and the adoption of fiscal discipline. Finally, the third sub-sample 2001-10 is motivated by the transition to an inflation targeting regime as well as the period of disinflation and normalisation for the Turkish economy.

The notion of developing a leading indicator to predict real activity goes back to the work of Mitchell and Burns (1938). In a comprehensive analysis, Stock and Watson (1999) examine the cyclical behaviour of the main US macroeconomic time series over the period 1946-96. They categorise the behaviour of 71 economic time series into leading, lagging and coincident indicators. In another contribution, Stock and Watson (2003) provide an analysis for the role of asset prices in forecasting output and inflation for seven OECD countries over the period 1959-99. As those authors note, much of the research on using asset prices for forecasting purposes was motivated by the apparent instability in forecasts of output and inflation based on the performance of monetary aggregates or the (non-expectational) Phillips curve during the 1970s and early 1980s. Among their salient results is that asset prices are more useful for forecasting inflation than output. While the behaviour of individual forecasts tends to be unstable, combination forecasts appear to work well in circumventing the instability problems.

The literature on developing leading indicators for emerging economies is more recent.¹ Up until the last decade, high levels of volatility, structural shifts and changes in policy regimes have made identifying leading indicators for emerging economies difficult. Chauvet (2000) derives leading indicators for inflation in Brazil over two periods, the first

corresponding to the post “Real Plan” period of 1994-99 and the second corresponding to a longer period of 1980-99 to account for changes in policy regimes in Brazil. Chauvet (2001) develops an indicator of Brazilian GDP at the monthly frequency by using a Markov switching dynamic factor model based on a set of variables that display coincident movements with changes in real GDP across three different periods. Chauvet and Morais (2008) however use a time-varying autoregressive probit model for predicting recessions in Brazil. Atabek et al. (2005) develop a composite leading indicator for the Turkish economy using the OECD methodology for the period 1988-2003.

Understanding the role of alternative institutional arrangements on aggregate economic activity is also more recent. Altug et al. (2012) examine the impact of alternative institutional arrangements such as overall governance and central bank independence on average business cycle characteristics for a large set of developed, emerging, and transition economies. Carvalho Filho de (2011) examines the role of inflation targeting in affecting economic performance for emerging economies during the recent global financial crisis. Kara (2006) provides a discussion of the process by which Turkey has moved from a regime of implicit inflation targeting to a full fledged inflation targeting regime. However, none of these studies examine the issue of identifying leading indicators under alternative policy regimes. In their study, Leigh and Rossi (2002) state that one of their objectives is to identify the variables most useful for forecasting inflation and real activity during the transition to an inflation targeting regime. However, since their sample ends in 2002, it does not permit a thorough identification of leading indicators during the period of transition to this regime which occurred during 2002-06, or under the formal inflation targeting regime itself after 2006.

In our analysis, we determine both individual leading indicators that are useful for forecasting industrial production growth and changes in consumer price inflation across different horizons. We also examine combination forecasts such as the trimmed mean and median of all the forecasts. Following Leigh and Rossi (2002), we also consider the median of the top five forecasts for predicting each variable. We uncover an important role for asset prices that capture expectational phenomena and policy interest rates in predicting IP growth and changes in CPI inflation at different horizons for the second and third sub-samples. This role however is more pronounced for changes in inflation than it is for IP growth, especially after the transition to formal inflation targeting in 2006. By contrast, changes in nominal and real monetary aggregates, and business sentiment indicators tend to be among the important predictors of IP growth and inflation changes in the first sub-sample. By focussing on the three sub-samples characterised by alternative policy regimes, our results provide evidence on the changing dynamics of the Turkish economy for the period 1988-2010.

The remainder of this paper is organised as follows. Section 2 presents the methodology while Section 3 describes the data. The results regarding the bivariate forecasts are presented in Section 4, which also provides a discussion of the results in view of the Turkish experience. Section 5 describes the combination forecasts and Section 6 concludes.

2. Methodology

Our methodology follows Stock and Watson (2003), and Leigh and Rossi (2002). Our goal is to develop forecasting models for changes in real activity and inflation using a

sample of monthly observations. We measure real activity by the industrial production index (IP) and the price level by the consumer price index (CPI). In contrast to real GDP, the choice of industrial production as a measure of real activity is due to its availability on a monthly basis.² The forecasting models examine the role of a candidate predictor, X_t , for forecasting the variable of interest h period ahead y_{t+h}^h . We consider horizons of $h = 1, \dots, 12$ for both variables, though we report results only for $h = 3, 6, 9, 12$. The model that we examine can be written as follows:

$$y_{t+h}^h = \mu + \alpha(L)y_t + \beta(L)X_t + \epsilon_{t+h}^h, \quad (1)$$

where $\alpha(L)$ and $\beta(L)$ are lag polynomials. All the forecasting models include the own lags of the dependent variable, y_t . They differ with respect to the candidate predictor that is considered. This approach differs from the standard approach of estimating one-step predictions and then iterating forward to obtain the h -step ahead forecasts. By keeping the estimation and forecast period the same, this approach has the advantage of reducing the specification error in the one-step ahead model.

The dependent variables were transformed to be stationary. We ran Augmented Dickey Fuller (ADF) tests for the entire sample period of 1988:1-2010:12. We fail to reject the null hypothesis of a unit root for the log of industrial production and the CPI. However, we also find evidence against the stationarity of the inflation series itself in that we are not able to reject the null hypothesis of a unit root for the log difference for the CPI. This suggests that the appropriate variable for the forecasting exercise is changes in inflation, and not inflation itself. Leigh and Rossi (2002) reject the null hypothesis of a unit root in the log difference of the CPI at the 1% level based on the ADF test. However, they find that the pseudo out-of-sample forecasting results tend to be more accurate for the second differences of the (log of the) CPI (the first difference of inflation) and report only those results. This is also the approach that we follow in this paper. The variable to be forecasted, y_t , is thus defined as the growth rate of industrial production or alternatively, changes in CPI inflation, both measured at annual rates. The multi-step forecasts investigate the predictability of the log of the level of the variable, after imposing the $I(1)$ or $I(2)$ transformations. For IP growth, this is $y_{t+h}^h = (1200/h) \log(IP_{t+h}/IP_t)$ and for CPI inflation, it is $y_{t+h}^h = (1200/h) \log(CPI_{t+h}/CPI_t) - 1200 \log(CPI_t/CPI_{t-1})$.

Previous studies have considered second differenced versions of the CPI, as inflation has tended to be a persistent process. However, there is recent evidence suggesting that both inflation and inflation persistence have become low and stable processes in part of the sample period that we study. Indeed, for the period 2001:1-2010:12, we find evidence against the null hypothesis of a unit root for the log difference of the CPI. Oliveira and Petrassi (2010) examine the persistence of CPI inflation for 23 industrial and 17 emerging economies in a sample that begins in 1995 and find that even countries that experienced near “hyperinflation” such as Argentina, Brazil, Bolivia, Peru, Mexico, Turkey, Israel and Poland have witnessed a decline in the persistence of their inflationary processes.³ Even if this phenomenon holds for Turkey, using changes in CPI inflation as the relevant variable to be forecasted improves the forecasting performance in the disinflationary period since 2002.

The approach used in this paper is based on the pseudo out-of-sample forecasting proposed by Stock and Watson (2003).⁴ The model estimation and selection are recursive in that they use all available prior data as the forecasting exercise proceeds through time. We

conduct our pseudo out-of-sample forecasting exercise for three separate periods to account for changes in the policy regime in Turkey over the greater sample period 1988-2010. We take the first sub-sample to correspond to the period 1988:1-2000:12, the second sub-sample to correspond to 1996:1-2005:12, and the third sub-sample to correspond to the period 2001:1-2010:12. Thus, for the first sub-sample the pseudo out-of-sample forecasting exercise begins in 1993:1 and continues until 2000:12; for the second sub-sample it begins in 2001:1 and continues until 2005:12; and, for the third sub-sample, it begins in 2006:1 and continues until 2010:12. Thus, the first forecast for each sub-sample is approximately based on five years of data, after accounting for differencing and initial conditions, while the subsequent forecasts are based on samples that increase over time. At each stage of the forecasting exercise, the lag lengths in the benchmark model and the model with the candidate indicator for IP growth and changes in inflation are chosen to minimise the Akaike Information Criterion (AIC). The lag lengths of the polynomial for lagged values of the dependent variable, $\alpha(L)$, are chosen to be between zero and twelve while the lag lengths for the polynomial for the candidate indicator, $\beta(L)$, are chosen to be between one and twelve. We iteratively add exogenous variables including all their possible lagged values up to twelve lags and choose the optimal lag length by using AIC. To identify a leading indicator, we compare the mean squared forecast error (MSFE) of the autoregressive specification comprising own lags only with that of the specification which also includes the candidate exogenous variable and its lags. A leading indicator is identified if the relative MSFE of the specification which includes the candidate indicator together with the own lags of the variable compared to the specification which includes the own lags only of the variable itself is less than one.

3. Data

The universe of variables that are available for constructing leading indicators is potentially very large. Our choice of variables depends on: i) whether there are theoretical/empirical reasons for their predictive content; ii) their availability at the monthly frequency; and, iii) their sample length. We use indicators of real activity, monetary aggregates, asset prices, and responses from a survey of future economic conditions conducted by the Central Bank of the Republic of Turkey (CBRT). Table 1 provides a list of the variables used in our study, their sample period and their sources.⁵ A further description of the data is available in Annex A.

Our series include variables measuring:

- activity in the economy including capacity utilisation, electricity production, production of agricultural machines, production of buses, the unemployment rate, total employment, exports, imports, intermediate goods imports and VAT revenue;
- prices such as Consumer Price Index (CPI), Producer Price Index (PPI), the oil price index and the US CPI;
- measures of nominal and real monetary aggregates, including broad monetary aggregates and reserves at the central bank;
- asset prices including various interest rates, the return, price-earnings ratio and dividend yield on the Istanbul Stock Exchange ISE100 index, the spread between the Turkish sovereign rate and US T-bill rate, the return on foreign currency denominated Turkish bonds, the dollar and the real exchange rate, and the price of gold;

Table 1. **Series descriptions and sources**

Acronym	Description	Sample period	Source
lipi	Log of Index of Industrial Production	1988:1-2010:12	IFS ¹
cur	Capacity Utilisation Rate	1991:2-2010:12	Turkstat ² and CBRT ³
greldr	Log of Gross Electricity Production	1988:1-2010:12	OECD ⁴
trac	Log of Production of Agricultural Machinery	1988:1-2010:12	AMA ⁵
bus	Log of Production of Buses	1988:1-2010:12	AMA
unemp	Unemployment Rate	2001:1-2010:12	Turkstat
totemp	Log of Total Employment	2001:1-2010:12	Turkstat
exp	Log of Exports (in 2003 prices)	1988:1-2010:12	Turkstat
imp	Log of Imports (in 2003 prices)	1988:1-2010:12	Turkstat
inimp	Log of Intermediate Goods Imports (in 2003 prices)	1996:1-2010:12	Turkstat
lvat	Log of VAT Revenue	2001:1-2010:12	RTMF ⁶
rvat	Log of Real VAT Revenue (in 2005 prices)	2001:1-2010:12	–
lcpi	Log of Consumer Price Index (2005=100)	1988:1-2010:12	IFS
lppi	Log of Producer Price Index (2005=100)	1988:1-2010:12	IFS
lop	Log of Oil Price (UK Brent - in USD)	1988:1-2010:12	IFS
rlop	Log of Real Oil Price (UK Brent - in 2005 prices)	1988:1-2010:12	–
uscpi	Log of US CPI (2005=100)	1988:1-2010:12	FRED ⁷
lm1	Log of Money Supply: M1 (in TRY)	1988:1-2010:12	CBRT
lm2	Log of Money Supply: M2 (in TRY)	1988:1-2010:12	CBRT
lm2y	Log of Money Supply: M2 + FX Deposits (in TRY)	1988:1-2010:12	CBRT
lm3	Log of Money Supply: M3 (in TRY)	1988:1-2010:12	CBRT
lm3y	Log of Money Supply: M3 + FX Deposits (in TRY)	1988:1-2010:12	CBRT
rlm1	Log of Real Money Supply: M1 (in 2005 prices)	1988:1-2010:12	–
rlm2	Log of Real Money Supply: M2 (in 2005 prices)	1988:1-2010:12	–
rlm2y	Log of Real Money Supply: M2+ FX Deposits (in 2005 prices)	1988:1-2010:12	–
rlm3	Log of Real Money Supply: M3 (in 2005 prices)	1988:1-2010:12	–
rlm3y	Log of Real Money Supply: M3 + FX Deposits (in 2005 prices)	1988:1-2010:12	–
onir	Interest Rate: Overnight (% p.a.)	1988:1-2010:12	OECD
dr	Interest Rate: Discount (% p.a.)	1988:1-2010:12	IFS
depo3m	Interest Rate: 3-Month Deposit (% p.a.)	1988:1-2010:12	CBRT
traucrate	Interest Rate: Treasury Auction Rate (% p.a.)	1988:1-2010:12	OECD MEI ⁸
ex-rate	Log of Average USD/TRY Nominal Exchange Rate	1988:1-2010:12	IFS
rex-rate	Log of Real Effective Exchange Rate	1988:1-2010:12	CBRT
ise100	Log of Stock Price	1988:1-2010:12	CBRT
rise100	Log of Real Stock Index (in 2005 prices)	1988:1-2010:12	–
is-pe	Price-Earnings Ratio on ISE100	1996:1-2010:12	ISE ⁹
divpr	Dividend Yield on ISE100	1988:1-2010:12	ISE
embi+	Log of JP Morgan EMBI Index for Turkey	1999:7-2010:12	WB ¹⁰
irspread	Spread: Sovereign interest rate - US T-bill Rate	1996:6-2010:12	WB
gold	Log of Gold Price (in USD)	1988:1-2010:12	IFS
rgold	Log of Real Gold Price	1988:1-2010:12	–
lover	Log of Overdrafts	1988:1-2010:12	CBRT
lirescb	Log of Central Bank's Gross FX Reserves	1988:1-2010:12	CBRT
lires-gold	Log of International Reserves: Gold	1988:1-2010:12	CBRT
lires	Log of Gross International Reserves	1988:1-2010:12	CBRT
prosp-exp	Balance of responses on export possibilities	1988:1-2010:12	OECD MEI
stocks-fin	Balance of responses on monthly stocks of finished goods	1988:1-2010:12	OECD MEI
emp-tend	Balance of responses on 3-month trend for total employment	1988:1-2010:12	OECD MEI

Table 1. **Series descriptions and sources** (cont.)

Acronym	Description	Sample Period	Source
new-orders	Balance of responses on 3 month trend for new orders from the domestic market	1988:1-2010:12	OECD MEI

Sources:

1. IFS: IMF International Financial Statistics.
2. Turkstat: Turkish Statistical Institute.
3. CBRT: Central Bank of the Republic of Turkey.
4. OECD: OECD Statistics.
5. AMA: Automotive Manufacturers' Association.
6. RTMF: Republic of Turkey Ministry of Finance.
7. FRED: Federal Reserve Bank of St. Louis Economic Database.
8. OECD MEI: OECD Main Economic Indicators.
9. ISE: Istanbul Stock Exchange.
10. WB: World Bank Global Economic Monitor.

- survey responses obtained from the Central Bank of the Republic of Turkey Business Tendency Survey (BTS) for prospects for exports, future employment trends, the stocks of finished goods and new orders for the domestic market.⁶

The variables that we use are similar to those examined by Stock and Watson (2003), and Leigh and Rossi (2002). However, our study also includes core variables seeking to measure real activity in the economy. In this respect, our study has more in common with Chauvet (2001), who considers different measures of industrial production, capacity utilisation, real wages, compensated hours, retail sales, employment, the unemployment rate, fuel consumption and electricity consumption. The variables in our study can also be categorised in terms of whether they represent supply, demand, policy or expectational factors. Variables such as the capacity utilisation rate, the PPI, imports, especially imports of intermediate goods, and production of certain durable goods may represent supply side influences. Exports and the CPI may be indicative of demand side influences while revenue from the value-added tax may reflect effects from both the demand and supply sides.⁷ Policy variables are represented by interest rates, monetary aggregates or international reserves while market expectations are captured through variables measuring the return on the stock market, the return on foreign currency denominated Turkish bonds, or the spread between Turkish and US bonds. Finally, as in Atabek et al. (2005) or Chauvet and Morais (2008), we include survey measures of business sentiment on alternative aspects of real activity. Of these measures, the survey response about the next 3-month trend for total employment represents a supply-side variable in that it measures expectations about future output, which depends on future employment. By contrast, the survey responses regarding prospects for exports, stocks of finished goods and new orders in the domestic market represent demand side variables.⁸

Several transformations are applied to the explanatory variables. The first issue has to do with seasonal variation. As shown in Annex A, some of the variables were available from the source in seasonally adjusted form. For the remainder, we conduct tests of seasonality by regressing (a suitably differenced version of) the series on seasonal dummies. For those series that exhibit seasonal variation, we implement deseasonalisation using the TRAMO-SEATS procedure, which decomposes the observed series into trend, cyclical, seasonal and irregular components using an autoregressive integrated moving average (ARIMA) model-based approach. The impact of unusual events (such as moving

holiday effects like Muslim festivals of Sacrifice and Ramadan) and calendar effect variables such as trading day, leap year effect, and national holidays are also removed using the adjustments suggested in Atabek et al. (2009). In some cases, logarithms are taken of the original variables which are structured in levels. Differencing or second differencing is used to remove trends from persistent variables. For some variables such as interest rates or dividend yields, it is unclear whether they should be included as levels or in difference form. Hence, we include both versions for such variables. Real and nominal versions of various quantities are also included in our analysis. Models with nominal rigidities such as the New Keynesian model (see for example, Gali, 1999) predict that nominal quantities may have an effect over and above those of real variables.

4. Results

In this section, we describe the selection of leading indicators for IP growth and changes in inflation for the three different forecast periods. We also provide a discussion of the results in light of the existing literature and the developments in the Turkish economy over the relevant sample period. Prior to analysing the results in these tables, it is important to note that some of the improvements in forecasting performance may have to do with sampling variability as opposed to statistical significance of the leading indicators. It is possible to formally test the null hypothesis that the relative MSFE is equal to one versus the alternative that it is less than one using the Clark and McCracken (2001) approach. Alternatively, standard errors can be computed for the MSFE using the approach in Diebold and Mariano (1994), for example. However, there are conceptual and computational issues regarding both approaches.⁹

4.1. IP growth

The pseudo out-of-sampling forecasting results pertain to the sub-samples of 1988-2000, 1996-2005, and 2001-2010, with the respective corresponding forecast periods being 1993:1-2000:12, 2001:1-2005:12, and 2006:1-2010:12. From now on, we will primarily refer to the relevant forecast period when describing our results. The results for the 2006:1-2010 forecast period are given in Table 2 while Tables A.1 and A.2 provide the results for the two earlier forecast periods. Since some of the indicators are available for shorter samples, the results for the first two forecast periods are based on a slightly smaller set of potential indicators.

1993:1-2000:12 forecast period

There are few indicators that lead to significant improvements at most horizons. Of these indicators, changes in the foreign exchange reserves at the central bank (difference of “lirescb”) provide an improvement in the forecast of IP growth relative to the autoregressive benchmark of up to 7% at the 3-month horizon as well as inducing more minor improvements at the remaining horizons. Changes in the supply of nominal and real M1 (differences of “lm1” and “rlm1”) induce improvements of 10-11% at horizons from 3 to 6 months. There is some evidence for the role of changes in the supply of nominal and real M2, as well as changes in real M2Y and M3 (differences of “lm2”, “rlm2”, “rlm2y”, and “rlm3”) for providing improvements in the forecasts of IP growth relative to the autoregressive benchmark at different horizons but such improvements are minor. There is also some evidence for the role of asset prices in the short run in that the nominal return on the ISE100 (differences of “ise100”) leads to improvement of 8% at the 3-month horizon.

Table 2. **IP growth: Pseudo out-of-sample forecasting accuracy, 2006:1-2010:12**

Forecast horizon		$h = 3$	$h = 6$	$h = 9$	$h = 12$
Univariate autoregression		Root mean squared forecast error			
		25.79	19.08	15.98	13.92
Bivariate forecasts		MSFE relative to univariate autoregression			
Indicator	Transformation				
cur	d	1.01	0.99	1.00	1.00
greipr	d	1.05	1.05	0.98	1.00
trac	d	1.08	0.96	1.01	1.02
buses	d	1.09	1.10	1.03	1.00
unemp	–	1.63	1.43	1.29	1.16
unemp	d	1.30	1.18	1.16	1.01
totemp	d	1.60	1.14	1.07	1.01
exp	d	1.45	1.17	1.01	0.93
imp	d	1.20	1.15	1.02	1.01
inimp	d	1.15	1.11	1.03	1.00
lvat	d	1.14	1.07	1.02	1.04
lvat	2d	1.11	1.19	1.05	1.01
rlvat	d	1.04	1.10	1.07	1.10
lcpi	d	1.25	1.19	0.98	1.00
lcpi	2d	1.09	1.15	1.02	1.01
lppi	d	1.08	1.01	1.02	1.05
lppi	2d	1.07	1.01	1.03	0.98
lop	d	1.20	1.05	1.09	1.07
lop	2d	1.05	0.99	1.00	1.00
rlop	d	1.18	1.03	1.08	1.08
uscpi	d	1.73	1.16	1.64	0.99
uscpi	2d	1.34	1.02	1.01	1.00
lm1	d	1.05	1.05	1.08	1.15
lm1	2d	1.00	0.99	1.01	0.99
lm2	d	1.22	1.05	1.10	1.13
lm2	2d	1.13	1.01	1.00	1.00
lm2y	d	1.21	1.08	1.05	1.06
lm2y	2d	1.18	1.00	1.00	0.99
lm3	d	1.24	1.09	1.03	1.06
lm3	2d	1.09	1.06	1.01	1.00
lm3y	d	1.22	1.08	1.06	1.05
lm3y	2d	1.22	1.01	1.01	1.00
rlm1	d	1.02	0.99	0.99	1.10
rlm2	d	1.17	1.06	1.03	1.02
rlm2y	d	1.23	1.06	1.01	1.14
rlm3	d	1.16	1.04	0.97	1.01
rlm3y	d	1.23	1.06	1.04	1.12
onir	–	1.19	1.13	1.06	1.03
onir	d	1.16	1.09	0.95	1.00
dr	–	1.19	1.12	1.11	1.10
dr	d	1.07	1.00	1.00	1.00
depo3M	–	1.22	1.11	1.07	1.02
depo3M	d	1.21	1.10	1.06	1.00
traucrate	–	1.24	1.13	1.02	1.01
traucrate	d	1.21	1.14	1.02	0.99
ex-rate	d	1.23	1.03	1.03	1.01
rex-rate	d	1.25	1.00	1.01	1.01
ise100	d	1.03	1.01	0.96	1.00
rise100	d	1.03	1.00	0.93	1.01
ise-pe	–	0.99	1.01	0.99	0.98

Table 2. **IP growth: Pseudo out-of-sample forecasting accuracy, 2006:1-2010:12** (cont.)

Forecast horizon		$h = 3$	$h = 6$	$h = 9$	$h = 12$
Univariate autoregression		Root mean squared forecast error			
		25.79	19.08	15.98	13.92
Bivariate forecasts		MSFE relative to univariate autoregression			
ise-pe	d	0.97	0.98	1.00	0.99
divpr	–	1.16	1.34	1.47	1.27
divpr	d	1.17	1.00	1.00	1.00
embi+	d	1.07	0.93	0.96	0.97
irspread	–	1.10	1.02	0.98	0.92
irspread	d	1.11	0.99	0.98	0.98
gold	d	1.40	1.50	1.27	1.08
gold	2d	1.04	1.03	1.03	1.00
rgold	d	1.39	1.45	1.17	1.07
lover	–	1.25	1.08	1.06	1.11
lover	d	1.23	1.05	1.01	1.04
lirescb	–	1.34	1.33	1.18	1.07
lirescb	d	1.12	0.99	1.02	1.00
lires-gold	–	1.28	1.32	1.32	1.30
lires-gold	d	1.15	0.99	1.02	1.01
lires	–	1.52	1.77	1.94	1.39
lires	d	1.05	0.96	1.02	1.01
prosp-exp	–	1.04	0.98	0.93	1.05
stock-fin	–	1.38	1.19	1.30	0.96
emp-tend	–	1.26	1.12	0.91	0.96
new-orders	–	1.06	1.10	0.94	0.93

Note: Bold indicates a relative MSFE < 1.

The survey responses to the question regarding new orders in the domestic market (“new-orders”), which represents a demand-side variable, leads to an improvement of 13% at the 3-month horizon. Changes in nominal and real oil prices (differences of “lop” and “rlop”) lead to improvements relative to the autoregressive benchmark of 12-13% at a horizon of a year, attesting to supply-side influences on the economy over the longer run.

2001:1-2005:12 forecast period

In this case, changes in the Treasury auction rate (difference of “traucrate”) is the only indicator that provides improvements relative to the autoregressive benchmark at all horizons, such improvements being around 30% at 9 to 12 months. Asset prices such as the nominal and real return on the ISE100 (differences of “ise100” and “rise100”) and changes in the nominal and real gold price (differences of “gold” and “rgold”) matter for forecasting IP growth at a horizon of a year and less. The very substantial reductions in the MSFE of IP growth attributed to the nominal and return on the ISE100 relative to the autoregressive benchmark can be rationalised by the large fluctuations observed in the price of the ISE100 observed during the 2000-01 crisis.

Trade-related variables such as prospects for exports (“prosp-exp”) provide improvements of 17-21% in the relative MSFE of IP growth at 6 to 9 month horizons, respectively, while changes in intermediate inputs provide an improvement of 11% at a horizon of 9 months. It is worth noting that Atabek et al. (2005) include imports of intermediate goods in their composite leading indicator for Turkey constructed over the period 1985-2003. The role for imports of intermediate goods arises from the structure of Turkish manufacturing, which is heavily dependent on such imports. (See, for example,

Yükseler and Türkan, 2008.) Thus, an increase in intermediate goods imports today translates into higher IP growth 9 months ahead.

2006:1-2010:12 forecast period

There is no single variable that provides an improvement relative to the autoregressive benchmark for all horizons for this forecast period. However, among the variables that matter, there is more evidence for the role of asset prices. As an example, the EMBI+ return (difference of “*embi+*”) provides improvements to the IP growth forecast at several horizons, with the greatest improvement occurring at a 6-month horizon (7%). Likewise, changes in the interest spread rate on short-term Turkish government bonds relative to US government bonds (difference of “*irspread*”) leads to an improvement of 8% at the one-year horizon. There is also evidence for the role of the nominal and real return on the ISE100 (difference of “*rise100*”) and of changes in the overnight interest rate (difference of “*onir*”), these variables leading to improvements between 4-7% at the 9-month horizon.

There is also a role for indicators of business sentiment from the CBRT Business Tendency Survey as well as for changes in exports, especially at horizons of 9 months to a year, attesting to the role of indicators related to the real economy. However, we observe that the forecasting power of indicators such as the survey responses regarding as future employment tendencies (“*emp-tend*”), prospects for exports (“*prosp-exp*”), and new orders in the domestic market (“*new-orders*”) has diminished substantially in the last forecast period relative to the previous one. This may have to do with the experience of the 2008-09 financial crisis, which was largely external to the Turkish economy.

4.2. Changes in CPI inflation

As in the case for IP growth, we examine the determinants of changes in CPI inflation for three separate forecast periods. The results for the 2006:1-2010:12 forecast period are in Table 2, while Tables A.3 and A.4 contain the results for the earlier two forecast periods.

1993:1-2000:12 forecast period

There are multiple indicators that lead to improvements in the forecasts of inflation changes at all horizons relative to the autoregressive benchmark. The indicators that lead to some of the greatest improvements are given by the level and changes of producer price inflation (first and second differences of “*lppi*”), which induce improvements around 15-43% in forecasts of inflation changes at horizons 6 months to a year, and the survey responses to questions on prospects for exports (“*prosp-exp*”), stock of finished goods (“*stock-fin*”), employment trends (“*emp-tend*”), and prospects for new orders (“*new-orders*”), which induce improvements around 25-50% in forecasts of inflation changes at horizons of 6 months to a year. Changes in all of the real monetary aggregates (differences of “*rlm1*”, “*rlm2*”, “*rlm2y*”, “*rlm3*”, and “*rm3y*”) lead to improvements of 15-25% at horizons 6 months to a year. Changes in exports (differences of “*exp*”) also lead to improvements of 20-30% at horizons of 6 months to a year. Finally, there is some role for changes in the discount rate (difference of “*dr*”) and the dividend-price ratio on the ISE1000 (“*div-pr*”), especially at longer horizons.

The impact of these variables is evidence for the monetary factors that lie behind the high and chronic inflation of the 1990s in Turkey together with the high pass-through from producer to consumer prices. The strong role attributed to the responses to the survey questions also suggests that current and past developments were embedded in private agents’ expectations about the future course of the economy, which tend to have strong predictive power for changes in inflation six months or more into the future.

2001:1-2005:12 forecast period

For this forecast period, there still exist variables that help to predict inflation changes at multiple horizons but their forecasting power is lower. Interestingly, consumer price inflation in the US (differences of “uscpi”) has the strongest impact of inflation changes in Turkey at a horizon of a year, leading to a 34% reduction in the MSFE relative to the autoregressive benchmark. This most likely reflects the impact of low global interest rates in the post-2001 period, which have played a strong role in the disinflation process in Turkey during 2002-05.

Of the remaining variables, the growth rates (and their changes) of nominal and real monetary aggregates continue to matter as the variables that help to improve the forecasting performance of changes in CPI inflation at almost all horizons. In particular, changes in the growth rate of nominal M2 and M2Y (second difference of “lm2” and “lm2y”) and the growth rates of nominal M2Y and real M2, M2Y, M3, and M3Y (differences of “lm2”, “rlm2”, “rlm2y”, “rlm3”, and “rlm3y”) lead to improvements of 8-12% in the relative MSFE of changes of CPI inflation at different horizons. Other variables that improve the forecast of changes in CPI inflation include changes in interest rates such as the discount rate and the Treasury auction rate (differences of “dr” and “traucrate”) as well as the real return on the ISE100 (difference of “rise100”). We also find some role for changes in the growth rate of the nominal gold price (second difference of “gold”) at longer horizons.

2006:1-2010:12 forecast period

Table 3 shows that the level of PPI inflation is the variable that leads to the greatest improvement in the forecasts of inflation changes at 9 months to a year for the last forecast period, pointing to the relatively strong pass-through from producer to consumer prices. As we discuss below, since imported intermediate and final inputs account for a significant fraction of inputs for Turkish manufacturing, this finding also points to the role of capital inflows and exchange rate appreciation that Turkey experienced during the 2006-10 period. The growth in VAT revenue and its change (first and second difference of “lvat”) also appear as important predictors, leading to improvements of 30-35% at a horizon of a year. Since indirect taxes, especially taxes on imports, are an important source of tax revenue in Turkey, this finding again suggests a relationship between fiscal revenues and capital inflows, on the one hand, and inflationary pressures, on the other, for the Turkish economy at longer horizons.

Asset prices also play a much more prominent role for this forecast period. However, their effects tend to occur at longer horizons. The price-earnings ratio on the ISE100 (“ise-pe”) leads to improvements in the relative MSFE of inflation changes of 40% or more at horizons of nine months to a year. The overnight interest rate (“onir”), the three-month deposit rate (“depo3M”), and the discount rate (“dr”) are associated with reductions in the MSFE of changes in CPI inflation relative to the autoregressive benchmark of 34-60% at horizons of nine months to a year while the level of the Treasury auction rate (“traucrate”) leads to improvements of 15% at a horizon of one year.

Likewise, the level of overdrafts at the central bank (“lover”) are associated with 20-60% improvements in the relative MSFE of changes in inflation at horizons of six months to a year. Aside from these variables, there is some evidence for the effect of monetary aggregates such as changes in M2Y and M3Y (difference of “lm2y” and “lm3y”) at horizons of one year, suggesting that overall credit conditions continue to matter for inflation changes at relatively longer horizons.

Table 3. **CPI inflation: Pseudo out-of-sample forecasting accuracy, 2006:1-2010:12**

Forecast horizon		$h = 3$	$h = 6$	$h = 9$	$h = 12$
Univariate autoregression		Root mean squared forecast error			
		5.44	5.09	5.75	6.63
Bivariate forecasts		MSFE relative to univariate autoregression			
Indicator	Transformation				
lipi	d	1.69	2.02	1.50	1.53
lipi	2d	2.23	2.18	1.58	1.05
hp-ipi	–	4.03	5.83	4.72	4.96
cur	d	2.37	2.51	1.54	1.38
greipr	d	1.31	3.58	4.19	4.05
trac	d	1.01	1.04	1.07	1.00
buses	d	1.31	1.42	1.32	1.24
unemp	–	1.69	2.62	3.69	4.68
unemp	d	1.96	2.38	1.98	1.73
totemp	d	1.52	1.39	1.09	0.90
exp	d	2.11	3.08	3.90	3.74
imp	d	3.49	4.45	3.40	2.90
inimp	d	3.46	4.96	4.61	4.29
lvat	d	1.57	1.40	0.93	0.65
lvat	2d	1.40	1.18	0.98	0.69
rivat	d	1.85	2.03	1.38	1.32
lppi	d	1.01	0.63	0.38	0.18
lppi	2d	1.04	1.35	1.06	1.03
lop	d	1.00	1.70	3.53	3.71
lop	2d	0.99	1.00	1.00	1.07
rlop	d	1.03	2.44	3.42	3.49
uscpi	d	1.84	7.37	8.13	8.79
uscpi	2d	1.01	1.00	0.99	1.04
lm1	d	1.57	1.27	1.24	1.12
lm1	2d	1.00	1.53	1.35	0.99
lm2	d	1.24	1.87	1.53	1.34
lm2	2d	1.38	1.38	0.92	0.94
lm2y	d	1.67	1.48	1.16	0.77
lm2y	2d	1.73	1.75	1.70	1.43
lm3	d	1.76	1.89	1.29	0.90
lm3	2d	1.76	1.91	1.51	1.28
lm3y	d	1.64	1.49	1.11	0.76
lm3y	2d	1.69	1.73	1.68	1.51
rlm1	d	1.49	1.88	1.81	1.72
rlm2	d	1.15	1.41	1.18	0.99
rlm2y	d	1.25	1.27	1.14	0.97
rlm3	d	1.10	1.28	1.13	1.13
rlm3y	d	1.20	1.26	1.18	1.06
onir	–	1.59	1.02	0.63	0.40
onir	d	1.69	1.43	1.13	1.10
dr	–	1.40	1.54	0.86	0.66
dr	d	1.39	1.92	1.77	2.74
depo3M	–	1.90	1.47	0.91	0.59
depo3M	d	1.81	1.57	1.14	1.10
traucrate	–	1.77	1.52	1.15	0.85
traucrate	d	1.44	1.37	1.25	1.39
ex-rate	d	1.11	1.69	1.41	1.02
rex-rate	–	1.65	1.84	1.65	1.48
ise100	d	1.69	1.21	0.99	1.01
rise100	d	1.10	1.00	0.98	1.56
ise-pe	–	0.99	0.78	0.56	0.45

Table 3. **CPI inflation: Pseudo out-of-sample forecasting accuracy, 2006:1-2010:12** (cont.)

Forecast horizon		$h = 3$	$h = 6$	$h = 9$	$h = 12$
Univariate autoregression		Root mean squared forecast error			
		5.44	5.09	5.75	6.63
Bivariate forecasts		MSFE relative to univariate autoregression			
ise-pe	d	1.06	1.13	0.99	0.93
divpr	–	1.07	1.25	1.53	1.94
divpr	d	0.99	1.01	1.00	1.00
embi+	d	1.61	1.75	1.31	1.15
irspread	–	1.81	2.17	1.78	1.53
irspread	d	1.39	1.58	1.83	1.69
gold	d	0.96	4.61	4.59	1.27
gold	2d	1.05	1.02	1.04	1.03
rgold	d	1.20	4.24	4.53	1.26
lover	–	1.00	0.80	0.53	0.40
lover	d	1.01	1.03	0.96	1.07
lirescb	–	2.19	3.01	2.68	2.77
lirescb	d	1.55	2.88	1.72	2.03
lires-gold	–	1.10	1.07	1.04	1.34
lires-gold	d	0.96	1.04	1.03	1.02
lires	–	1.83	2.27	3.06	3.35
lires	d	1.83	2.31	2.64	1.95
prosp-exp	–	4.98	5.29	5.46	4.91
stock-fin	–	4.54	6.88	7.13	5.53
emp-tend	–	7.98	7.97	5.16	4.27
new-orders	–	4.44	6.02	3.95	3.21

Note: Bold indicates a relative MSFE < 1.

4.3. Discussion

It is worth comparing these results with those of others and relating them to developments in the Turkish economy during the 1988-2010 period. Our results indicate that the factors that account for both IP growth and changes in CPI inflation appear to have changed in the two forecast periods after 2001, namely, 2001-05 and 2006-10, relative to the first forecast period before 2001, 1993-2000.

IP growth

The indicators that provide an improvement on forecasts obtained from the autoregressive benchmark tend to change by the forecast period. In the first forecast period, we attribute a significant role to supply-side factors such the price of oil as well as to monetary factors such as changes in reserves and monetary aggregates while in the second forecast period, the Treasury auction rate emerges as an important predictor. The survey responses on different indicators of the future course of the economy from the CBRT Business Tendency Survey tend to matter for the first and second forecast periods.¹⁰ By contrast, asset prices tend to be important predictors during the second and third forecast periods.

Comparing these results with those of Leigh and Rossi (2002), we confirm the importance of asset returns and various interest rates for forecasting IP growth in the different forecast periods. However, we find that variables that are useful predicting IP growth at one horizon typically do not matter at other horizons. For the 2006-10 forecast period, we also attribute significant roles to the return on foreign-currency denominated

Turkish bonds represented by Turkey's EMBI+ return as well as the interest rate spread on Turkish bonds relative to US bonds for forecasting future IP growth. The predictive power of the EMBI+ return for Turkey points to the role of capital inflows in stimulating real activity in Turkey since 2001. As is well known, the Emerging Markets Bond Index (EMBI) for Turkey tracks total returns for its traded external or foreign currency denominated debt instruments. Along with other emerging economies, Turkey has witnessed declines in its risk premia in international capital markets during the recent decade. Combined with the increases in global liquidity overall, this has led to large increases in capital inflows to emerging economies such as Turkey.

The role of capital flows in affecting economic performance is studied by Calvo, Liederman and Reinhart (1999). Using a structural VAR analysis, Çulha (2006) finds that the relative role of “push” versus “pull” factors in determining inflows to Turkey has shifted after the 2000-01 crisis, with “pull” factors such as domestic interest rates, stock prices, inflation, domestic credit, etc., becoming more important. Çulha finds that while 22.5% of the variance on capital flows (measured as portfolio and short-term flows) can be accounted for by shocks to the real interest rate over the 1992:1-2001:12 period in Turkey, this quantity falls to 0.5% during 2002:1-2005:12. Likewise, the contribution of shocks to the Istanbul Stock Exchange Index ISE100 increases to 26.14% in the latter period relative to 0.97% in the earlier period. These findings appear to coincide with our findings in that changes in the EMBI index for Turkey as well as the indicators related to the stock market, figure among the most important indicators for predicting IP growth in the two forecast periods after 2001.

The fact that the interest rate spread on Turkish debt relative to US short-term also appears as another important predictor of IP growth in the forecast period 2006-10 shows that the changes in Turkey's cost of borrowing contributed to growth in real activity over this period. More generally, the role of various asset returns in affecting real economic activity is consistent with the process of normalisation experienced in Turkey during the latter half of the 2000s. As is well known, the period since 2002 has been characterised by falling interest rates, falling risk premia, and high rates of growth responding to an environment of economic and political stability in Turkey.¹¹

Aside from the role of asset prices, the role of reserves of the central bank and various monetary indicators in forecasting IP growth are also worth commenting on. For the 1993-2000 forecast period, changes in the foreign exchange reserves of the central bank together with various monetary aggregates matter for forecasting IP growth. This is consistent with the results of Leigh and Rossi (2002), who attribute a strong role for variables in predicting IP growth in the short-term as well as at some longer horizons. They attributed variables such as changes in the foreign exchange reserves of the central bank and commercial banks or the ratio of the foreign exchange reserves of commercial banks to the central bank's foreign exchange reserves. By contrast, there is no such role for reserves or monetary aggregates during the 2001-05 or 2006-10 forecast periods. We can understand these results by noting that large declines in real economic activity and crises during the pre-2001 period were typically accompanied by capital flight and the loss of foreign exchange reserves by both commercial banks and the central bank.¹²

CPI inflation

In the first forecast period corresponding to 1993-2000, the changes in the growth of nominal monetary aggregates together with the growth rates of real monetary aggregates figure as important determinants of changes in CPI inflation. This is consistent with the

results of Leigh and Rossi (2002). They find that the growth rates of monetary aggregates such as reserve money (M2Y, M3, M3Y), as well as changes in the growth rate of M1 lead to increases in the forecasting performance for changes in CPI inflation of 7-12% relative to the autoregressive benchmark. Likewise, they find that the growth rate of foreign exchange reserves of the central bank and commercial banks, the gross international reserves at the central bank, including the reserves of gold, and the first and second differences in the ratio of foreign-exchange denominated deposits to the M2Y monetary aggregate are associated with improvements in the forecasting performance of changes in CPI inflation on the order of 6-13%. It is well known that inflationary finance associated with monetising fiscal deficits was widely practiced in the pre-2001 period.¹³ Furthermore, Turkey typically experienced large increases in inflation as a result of the 1994 and 2000-01 financial crises, which were also accompanied by runs on the Turkish lira and a major decline in reserves of the central bank and the banking system as Turkey tried to maintain a managed floating exchange rate system.¹⁴

By contrast, the second and third forecast periods since 2001 have been characterised by fiscal discipline and a floating exchange rate regime adopted as part of the comprehensive reform package put into effect in May 2001. Furthermore, Turkey transited from an implicit inflation targeting regime to a formal inflation targeting regime in 2006, where the central bank has made achieving and maintaining price stability as its primary goal. As a consequence, the results in Table 3 for the third forecast period corresponding to 2006-10 suggest that short-term nominal interest rates such as the overnight interest rate, the discount rate, the three-month deposit rate as well as the return on the ISE100 have predictive power for inflation changes at a horizon of one year. The strong role for US consumer price inflation on the Turkish disinflation process displayed in Table A.4 for the forecast period 2001-05 suggests that the low inflation and low interest rates worldwide have also had a significant effect on inflationary dynamics in Turkey.

Various authors have stressed the role of exchange rate pass-through in determining inflationary dynamics for Turkey. Leigh and Rossi (2004) examine exchange rate pass-through for Turkey over the period 1994-2003 using a five-variable vector auto-regression (VAR) that includes oil price changes, IP growth, changes in the nominal exchange rate relative to US dollar, and wholesale and consumer price index inflation. They find that exchange rate pass-through is greater for the wholesale price index (WPI) compared to the consumer price index (60% versus 45% in a year). Likewise, they find that about 40% of the variance of the WPI inflation is accounted for by exchange rate shocks compared to 30% of the variance for CPI inflation, with another 20% of the variance of CPI inflation being explained by innovations to WPI inflation. Using a methodology similar to Leigh and Rossi (2004), Kara (2005) examines the impact of exchange rate pass-through by taking into account the changes in the exchange rate regime in the pre- and post-May 2001 periods. To account for the structure of production in the Turkish economy where imported inputs are used in both intermediate and final goods production processes, Kara (2005) considers a VAR with the output gap, import prices denominated in Turkish lira, private manufacturing prices, and core CPI inflation measures, which he estimates over the periods 1995:2-2001:4 and 2001:5-2004:9, respectively. He finds that the pass-through is much stronger for private manufacturing prices in both sub-periods, and that the magnitude and duration of pass-through has changed following the reforms undertaken in May 2001, including the adoption of a floating exchange rate regime.

These findings suggest that exchange rate pass-through is stronger for wholesale compared to consumer prices. Our results also indirectly confirm this fact in that what determines the dynamics of CPI inflation appears to be PPI inflation (or its changes). Indeed over both the forecast periods 1993-2000 and 2006-10, PPI inflation and its changes lead to significant reductions in the MSFE for changes in CPI inflation compared to the autoregressive benchmark. There is less evidence in this regard for the 2001-05 forecast period but this may have to do with the impact of the 2000-01 crisis, where the inflationary process was highly volatile. Thus, while our results do not attribute a direct role to exchange rate changes in determining the dynamics of inflation, we nevertheless show that pass-through from producer price inflation to consumer price inflation is an important determinant of the inflationary process in Turkey.

A variety of authors have argued that the output gap also figures as an important indicator of inflationary pressures in Turkey. Sarikaya et al. (2005) use a multivariate Kalman filtering approach to estimate potential output and the output gap. They argue that the output gap has contributed to the disinflation that occurred during 2002-04, and the importance of the output gap has been rising since 2001. In our analysis, we use a HP-filtered version of the output gap ("hp-ipi"), which is also the approach followed by Leigh and Rossi (2002). While we do not derive output gap measures based on a more economically meaningful approach, our use of three different forecast periods may help to capture the time variation in the determinants of inflation and output dynamics uncovered by Sarikaya et al. (2005). We fail to uncover a significant role for the output gap in predicting inflation changes, especially in the 2001-05 and 2006-10 forecast periods. There is some evidence that the output gap helps to reduce the MSFE of inflation changes relative to the autoregressive benchmark for the forecast period of 1993-2000 (see Table A.4). These results are, on the whole, consistent with those of Leigh and Rossi (2002), who uncover a minor role for the output gap on inflation changes for the forecast period 1992-2002. Sarikaya et al. (2005) find that the impact of interests rates on inflation and the output gap has risen considerably in the period after 2001, signifying a more important role for interest rate policy in "expectations management and output dynamics". Taken together, these results are not inconsistent with our conclusions regarding the enhanced role of interest rates and expectational phenomena in determining the dynamics of both output growth and inflation in the two forecast periods since 2001.

We conclude this section with some comments on identifying a set of leading indicators for the global financial crisis of 2008. While our analysis does not specifically examine this crisis, it is worth discussing some results in this regard. Frankel and Saravelos (2010) seek to determine leading indicators for the 2008-09 crisis for a broad cross section of countries. They find that the level of reserves in 2007 to be a "consistent and statistically significant leading indicator of who got hit by the 2008-09 crisis", a result which is also consistent with the earlier literature. They further argue that the level of reserves appears as a robust indicator of alternative measures of crisis incidence whereas exchange rate overvaluation matters when the crisis is defined in terms of the behaviour of the currency. One of the noteworthy findings of our study is that alternative measures of reserves have little predictive power for IP growth in the forecast period 2006-10. While Turkey suffered one of the largest declines in real activity compared to a variety of countries during 2008-09, it did not pursue a fixed exchange rate regime in contrast to other countries that displayed significant declines in real economic activity such as the Baltic countries. This may explain why our study does not attribute a greater importance to reserves in predicting real activity.

5. Combination forecasts

The lack of uniform predictability of bivariate relations has prompted researchers to examine the efficacy of combination forecasts. The notion behind combining forecasts based on individual variables is that the combined forecast will pool the information contained in the individual forecasts, and therefore, should be more efficient. Stock and Watson (2003) argue that the “optimal” combination forecasts discussed by Bates and Granger (1969), and Granger and Ramanathan (1984) often fail to perform better than simple combinations of forecasts such as their mean or median. Hence, they advocate using the trimmed mean and the median of the individual forecasts, which eliminate the impact of outliers on the resulting combination forecast. We also follow a suggestion of Leigh and Rossi (2002) and consider a two-stage forecast comprised of the median of the top five forecasts.

The approach to generating the combination forecasts is as before. We accumulate five years of data prior to any forecasting of the relevant series and start the forecasting exercise five years out in the relevant sub-samples to simulate a real-time forecasting situation. We then calculate the trimmed mean, where the lowest and the highest forecasts are trimmed to mitigate the influence of outliers, and median of all the individual forecasts as well as the median of the top five forecasts for each forecast horizon. Using this procedure, we generate a sequence of pseudo forecast errors $y_{t+h}^h - \hat{y}_{t+h}^h$ and compare the mean squared forecast error (MSFE) of the candidate indicator with the MSFE of the benchmark autoregressive specification. Notice that the top five indicators may change by forecasting horizon since there are less than five indicators which outperform the autoregressive benchmark at all horizons.

Tables 4 and 5 show that the relative performance of the forecasts appears to vary by the indicator that is being predicted. The median of the top five forecasts results in maximum reductions of 20% for IP growth for the first forecast period and 36% for the second forecast period. By contrast, the improvement in the relative MSFE of IP growth is lower when the third forecast period is considered. This is most likely due to the effect of the global financial crisis of 2008-09. Unlike the earlier crises that erupted due to domestic causes in a globalised environment, this crisis was due to external factors and hence, relatively difficult to predict based on primarily domestic indicators.

There is an opposite pattern for changes in CPI inflation. The improvement in the relative MSFE of inflation changes is at most 16% for the second forecast period, regardless of the horizon. By contrast, there are significant reductions in the MSFE of the forecast relative to the autoregressive benchmark for the first and third forecast periods, especially at longer horizons. In particular, there are improvements of nearly 75% for the forecast of inflation changes in the third forecast period at a horizon of a year. No doubt this phenomenon reflects the decline in inflation that occurs over the period 2006-10, which pertains to a period of disinflation and normalisation for the Turkish economy. The superior predictability of changes in CPI inflation using the combination forecasts is also demonstrated by Leigh and Rossi (2002). However, they obtain improvements in the range of 15-20% relative to the autoregressive benchmark over the forecast period of 1992-2002, attesting to the role of past inflation (or indexation) in determining current inflation performance during the period of high and volatile inflation for Turkey.

Figures 1 and 2 plot cumulated IP growth and cumulated changes in CPI inflation over three, six, nine and twelve months over the forecast period 2006-10. These figures also

Table 4. IP growth: Pseudo out-of-sample forecasting accuracy, combination forecasts

Forecast horizon	$h = 3$	$h = 6$	$h = 9$	$h = 12$
Combination forecasts	Relative MSFE			
1993:1-2000:12				
Trimmed mean of all forecasts	0.93	0.97	0.98	1.00
Median of all forecasts	0.97	0.99	0.98	1.00
Median of top 5 forecasts	0.80	0.87	0.88	0.95
2001:1-2005:12				
Trimmed mean of all forecasts	0.85	0.93	1.36	1.31
Median of all forecasts	0.98	1.01	1.00	0.99
Median of top 5 forecasts	0.78	0.86	0.64	0.67
2006:1-2010:12				
Trimmed mean of all forecasts	1.05	0.99	0.99	0.99
Median of all forecasts	1.09	1.00	1.00	1.00
Median of top 5 forecasts	0.98	0.96	0.89	0.92

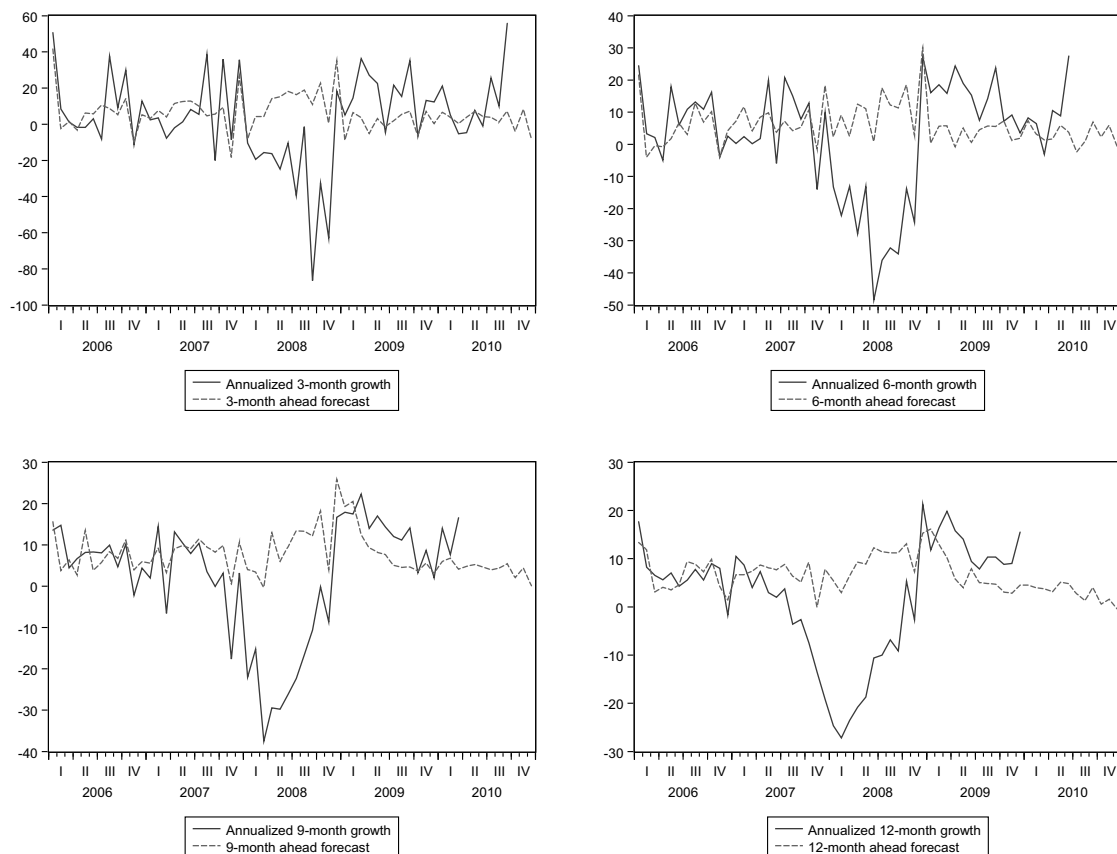
Table 5. CPI inflation: Pseudo out-of-sample forecasting accuracy, combination forecasts

Forecast horizon	$h = 3$	$h = 6$	$h = 9$	$h = 12$
Combination forecasts	Relative MSFE			
1993:1-2000:12				
Trimmed mean of all forecasts	0.89	0.85	0.86	0.84
Median of all forecasts	0.98	0.98	0.97	0.98
Median of top 5 forecasts	0.68	0.54	0.47	0.42
2001:1-2005:12				
Trimmed mean of all forecasts	0.97	0.97	0.97	1.00
Median of all forecasts	1.00	0.98	0.98	1.00
Median of top 5 forecasts	0.87	0.87	0.86	0.84
2006:1-2010:12				
Trimmed mean of all forecasts	1.06	1.10	0.90	0.78
Median of all forecasts	0.99	1.04	0.84	0.81
Median of top 5 forecasts	0.98	0.72	0.43	0.26

show the two-stage combination forecasts of IP growth and changes in inflation three, six, nine and twelve months ahead.¹⁵ We observe that the forecasts of IP growth over the forecast periods 1993-2000 and 2006-10 tend to be less accurate than for the remaining forecast period given in Figure A.2. This finding is in line with the results in Table 4, which show that the greatest improvements in the relative MSFE for IP growth using the median of the top five forecasts is for the 2001-05 forecast period, and it is most likely due to the existence of the 1994 financial crisis and 2008-09 global crisis.¹⁶

There are also differences in the efficacy of the combination forecasts for cumulated changes in CPI inflation, depending on the forecast period that is considered. Figure 2 shows that the combination forecasts tend to predict the future cumulated changes in inflation quite accurately over the forecast period 2006-10, especially at 9- to 12-month horizons. This is also evident from Table 5, which shows that the combination forecast induce the greatest improvements relative to the autoregressive benchmark at longer

Figure 1. IP growth, 2006:1-2010:12

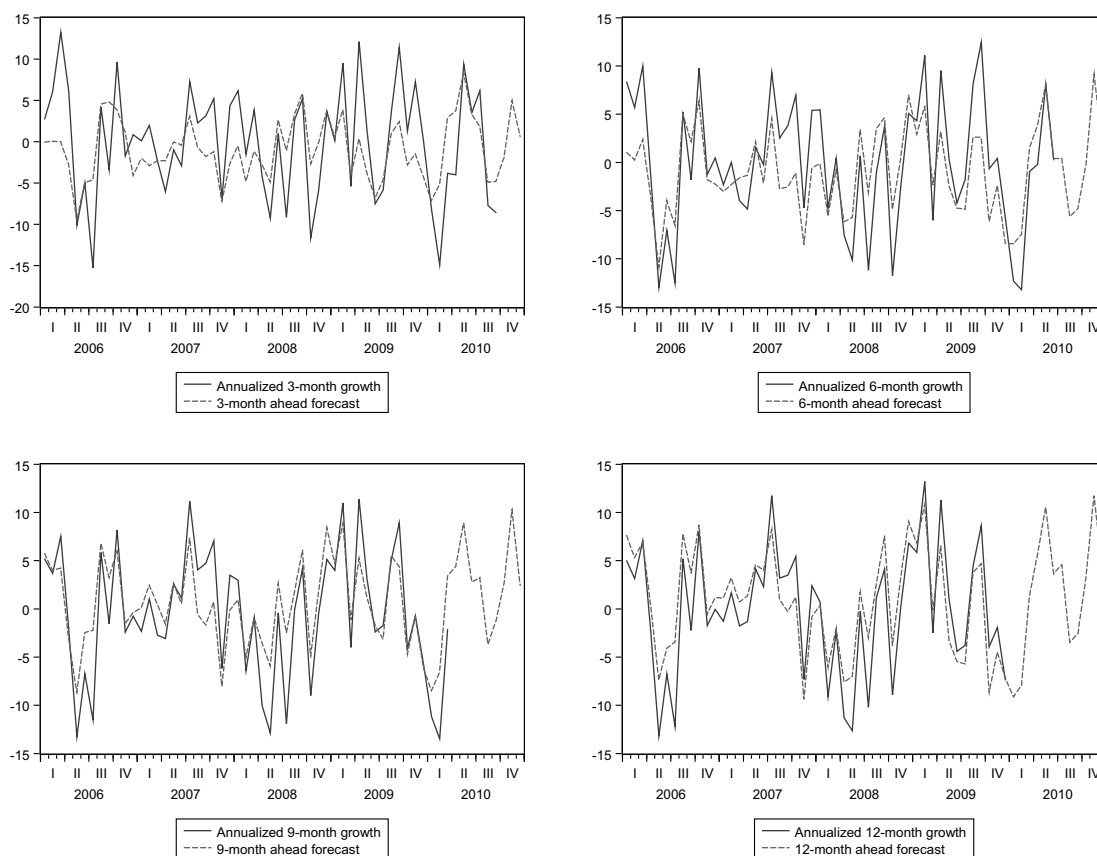


horizons. Figure A.3 shows that aside from the changes in inflation associated with the 1994 crisis, the combination forecasts also track fairly accurately the changes in inflation over the forecast period 1993-2000. The worst performance for the combination forecasts occurs for the forecast period 2001-05. As Figure A.4 shows, the combination forecasts that use data from 1996-2000 and beyond to forecast the disinflation in the 2002-06 period fare very poorly, especially in the earlier years. This finding highlights the importance of accounting for the changes in the policy regimes that occurred in May 2001.

6. Conclusion

In this paper, we have presented a systematic approach to identifying leading indicators for real activity and inflation in Turkey over the extended sample period 1988-2010. To our knowledge, our paper is the first to consider such a long sample and to examine the efficacy of a large number of candidate indicators across three different sub-samples that include two financial crises as well as a major globally induced recession. Our findings suggest that the types of indicators leading to improvements in the forecasts of IP growth and changes in inflation relative to an autoregressive benchmark have changed across the three separate forecast periods considered in this study.

Our results provide evidence of the changing dynamics of the Turkish economy in a period that includes significant policy reforms and institutional changes. In the first

Figure 2. **Changes in CPI inflation, 2006:1-2010:12**

forecast period, changes in monetary aggregates and business sentiment are important predictors of both changes in real activity and inflation. For the latter two forecast periods, we uncover a major role for asset prices that incorporate expectational phenomena and interest rates that reflect the policy stance in predicting IP growth and CPI inflation at different horizons. However, our results indicate that the gains to forecasting changes in inflation in the last forecast period beginning in 2006 using expectational and policy variables are much greater than the gains in forecasting IP growth. These results reflect the experience of a transition to a formal inflation targeting regime, which occurred formally in 2006. These findings are also indicative of a change in the dynamics of inflation from the first two forecast periods to the last forecast period, with expectational phenomena becoming much more important for the latter. They thus point to the importance of developing forward-looking models in understanding the impact of alternative policy choices on the behaviour of the Turkish economy.

One of the key issues in understanding macroeconomic performance in Turkey has to do with the role of capital flows. We fail to attribute a significant role to exchange rate changes for predicting either IP growth and changes in inflation across the different forecast periods that we consider. However, as we discuss in the text, the impact of producer price inflation and its changes together with changes in revenue from value-added taxes is indirect evidence for the role of capital inflows and the ensuing import surge

for determining changes in consumer price inflation in Turkey, especially for the last forecast period since 2006. Taken together, our results suggest that the factors that have determined both real activity and inflation performance in the 2001-post period and especially after 2006 are driven by expectational phenomena that are manifested in the behaviour of alternative financial variables and that also help to determine capital inflows to Turkey. The role that interest rates play also suggests that the decline in inflation that occurs after 2002 is achieved by anchoring expectations and maintaining credibility under an inflation targeting regime.

In this paper, we have only considered linear time series methods. Other approaches involve using nonlinear methods with regime shifts to account for the changes in the policy regimes observed in the Turkish economy over the period 1988-2010. While models with regime shifts have typically been used to model cyclical dynamics for developed and emerging economies by many studies,¹⁷ whether they can adequately capture the changing dynamics inflation remains an unanswered question.

Notes

1. There is a large literature involved in identifying early-warning indicators of banking and currency crises (see, for example, Goldstein and Turner, 1996; or Kaminsky and Reinhart, 1999). This literature arose in response to the experience of banking and currency crises, abrupt reversals in capital flows due to “Sudden Stop” phenomena, and issues of debt sustainability and proper fiscal management that emerging economies faced in the 1980s and 1990s. Uluceviz and Yildiran (2010) analyse whether, and how international interbank loans affected the probability of crises in the period 1980-2002.
2. This is consistent with the practice of the OECD for developing composite leading indicators of economic activity. See the OECD publication *OECD System of Composite Leading Indicators* (2008).
3. They examine a variety of empirical specifications to capture inflation dynamics, including models with lags of inflation with and without an output gap, New Keynesian Phillips curves with foreign exchange rates, and reduced forms derived from structural specifications that allow for some form of wage rigidity. They attribute their finding to the anchoring of expectations under inflation targeting regimes adopted by many industrial and emerging economies, and the commitment to price stability pursued by the Federal Reserve, the European Central Bank and other monetary authorities.
4. An alternative methodology is to use in-sampling techniques based on examining cross-correlations of a set of indicators with the variables in question, say, IP growth and CPI inflation, and Granger causality tests. As various authors have argued, however, such in-sampling techniques can lead to over-fitting in the sample at hand and provide little guidance regarding future predictive performance (see, for example, Stock and Watson 2003). Chauvet (2000) also emphasises the role of out-of-sample techniques for developing a leading indicator of inflation in Brazil that can be used as an aid in real-time monitoring of monetary policy.
5. We start our sample in 1988:1 to account for the availability of the indicators of the CBRT *Business Tendency Survey*, as discussed below.
6. The CBRT *Business Tendency Survey* (BTS) was initiated in 1987 and it includes the assessments of senior managers in the manufacturing industry. The monthly survey of which we make use initially contained a total of 28 questions but these were reduced to 22 questions after a harmonisation of the BTS with international standards in 2006. See www.tcmb.gov.tr/ikt-yonelim/BTS-Methodology.pdf.
7. The implementation of the value-added tax in Turkey is in the form of a “credits” system. That is, a tax is levied on the total value of sales at each stage of production and a credit for any VAT is paid on inputs in production. See, for example, Metcalf (1995) or Price WaterhouseCoopers (2004).
8. Atabek et al. (2005) conduct a wider search regarding the role of survey responses contained in the entire CBRT *Business Tendency Survey*. In this study, we use the four variables that they find to be most important for constructing a composite leading indicator (CLI) for the Turkish economy over the period 1988-2003.

9. As Stock and Watson (2003) note, the Clark-McCracken null distribution is computed under the assumption of constant lags in the out-of-sample forecasting exercise whereas in our approach, the lags change as the model is re-estimated with the accumulation of additional data. With regards to computing standard errors for the MSFE, this typically requires a long time series of predictions based on regression estimates.
10. This latter finding is in line with that of Atabek et al. (2005), who make use of these indicators in the construction of their composite leading indicator for the Turkish economy over the period 1986-2003.
11. Çulha (2006) provides another indicator of this normalisation process based on the impact of an increase in US interest rates on capital flows to Turkey. He argues that in the period 1992:1-2001:12, an increase in US interest rates was accompanied by an increase in capital flows to Turkey, as low US interest rates coincided with the periods in which Turkey itself experienced financial crises (or there were contagious effects of the East Asian and Russian crises). By contrast, in the period after 2002, an increase in US interest rates is accompanied by a capital outflow from Turkey, as predicted by standard economic analysis.
12. In the pre-2001 period, Turkey followed a crawling peg or managed floating exchange rate regime. The IMF-supported Exchange Rate Based Stabilisation programme adopted in 2000 sought to anchor inflationary expectations through a nominal exchange rate target. However, with the collapse of this programme in the aftermath of the severe banking and financial crisis in February 2001, Turkey moved to a regime of floating exchange rates.
13. For a discussion of the factors that led to the 1994 financial crisis, including policy mistakes, see Özatay (1996).
14. See, for example, Özatay and Sak (2002) for a discussion of the events surrounding the 2000-01 crisis in Turkey.
15. The relevant graphs for the forecast periods 1993-2000 and 2001-05 are in Figures A.1-A.4.
16. Figure A.2 also shows that data from 1996-2000 and beyond are much worse at predicting the recovery after 2002, especially at longer horizons. This finding is due to the changes in the policy regime after 2002, which led to a surge in real activity and growth for the Turkish economy.
17. As a recent example, see Altug and Bildirici (2012).

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ANNEX A

In this Annex, we describe the variables used in our study and the data sources in more detail. SA denotes series that were seasonally adjusted at the source, NSA denotes series that are available in seasonally unadjusted form.

IPI:	Seasonally adjusted IPI series. Base year = 2005. SA
CUR:	Capacity Utilisation Rate (CUR) of the Manufacturing Industry. Prior to 2007, only Turkstat was publishing the series CUR – Public and Private Enterprises and the combined total CUR series. Following the memorandum signed by Turkstat and Central Bank of the Republic of Turkey (CBRT), CBRT started publishing the new CUR series after 2007 after eliminating the Public and Private Enterprises differentiation. For the pre-2007 period, we use the CUR series provided by Turkstat, for the post-2006 period we use the series provided by the CBRT. NSA
GRELPR:	Monthly gross electricity production data. OECD Monthly Economic Indicators. SA
TRAC:	Monthly production of tractors as provided by Automotive Manufacturers Association (AMA). NSA
BUS:	Monthly production of buses as provided by Automotive Manufacturers Association (AMA). NSA
UNEMP:	Prior to 2005, only quarterly unemployment rate series was published. After 2005, monthly series was released on unemployment. To generate monthly series for the pre-2005 period, we interpolated the quarterly unemployment rates by using compounded monthly growth rates for each quarter, thus generating monthly series for 2001-2010. NSA
TOTEMP:	Prior to 2005, only quarterly total employment series was published. After 2005, monthly series was released. To generate monthly series for the pre-2005 period, we interpolated the quarterly total employment by using compounded monthly growth rates for each quarter, thus generating monthly series for the 2001-2010. NSA
EXP:	Total Exports deflated by Export Unit Value Index. Base year = 2003. NSA
IMP:	Total Imports deflated by Import Unit Value Index. Base year = 2003. NSA
INIMP:	Total Intermediate Goods Imports deflated by Import Unit Value Index. Base year = 2003. NSA
VAT:	Total monthly VAT revenue series was obtained from General Directorate of Budget and Fiscal Control of the Ministry of Finance. NSA
CPI:	Consumer Price Index. Base year = 2005. NSA
PPI:	Producer Price Index. Base year = 2005. NSA

OP:	UK Brent Market Oil Price (in USD). NSA
USCPI:	Seasonally adjusted US CPI. Base year = 2005. SA
M1:	Weekly monetary aggregates provided by CBRT. If the data correspond to the last day of the month, these data are used. Otherwise, we linearly interpolate the neighbouring data to set the last day of the month datum. NSA
M2:	Weekly monetary aggregates provided by CBRT. If data correspond to the last day of the month, this datum is used. Otherwise, we linearly interpolate the neighbouring data to set the last day of the month datum. NSA
M2Y:	M2 + FX deposits. Weekly monetary aggregates provided by CBRT. If the data correspond to the last day of the month, these data are used. Otherwise, we linearly interpolate the neighbouring data to set the last day of the month datum. NSA
M3:	Weekly monetary aggregates provided by CBRT. If the data correspond to the last day of the month, these data are used. Otherwise, we linearly interpolate the neighbouring data to set the last day of the month datum. NSA
M3Y:	M3 + FX deposits. Weekly monetary aggregates provided by CBRT. If the data correspond to the last day of the month, these data are used. Otherwise, we linearly interpolate the neighbouring data to set the last day of the month datum. NSA
ONIR:	Overnight Interbank Interest Rates. OECD Monthly Economic Indicators. NSA
DR:	End of Period Discount Rate. NSA
DEPO3M:	Averages of maximum deposit rates as reported by banks to be effective during the month of reporting and weighted by volume of deposits and number of days of maturity. NSA
TRAUCRATE:	Yearly annualised interest rates of Treasury discounted auctions. NSA
EX-RATE:	Period average market rate of USD in terms of TRY. NSA
REX-RATE:	CPI based real exchange rate. Base year = 2003. NSA
ISE100:	ISE National-100 index. Daily ISE100 closing values are used and the last day of each month is treated as the monthly value for the respective index value. In case the last day is missing, we linearly interpolate the neighbouring data to set the last day of the month datum. NSA
IS-PE:	Price-earning ratio on the ISE National-100 index. Net earnings are calculated based on quarterly financial tables. NSA
DIVPR:	Dividend yield on ISE100. NSA
IRSPREAD:	Sovereign Bond Interest Rate Spreads, basis points over US Treasuries. NSA
EMBI+:	J.P. Morgan Emerging Markets Bond Index for Turkey. The regular EMBI index covers U.S.dollar-denominated Brady bonds, loans and Eurobonds. The EMBI+ expands upon J.P.Morgan's original Emerging Markets Bond Index (EMBI), which was introduced in 1992 and covered only Brady bonds. NSA
GOLD:	London price of troy ounce of gold. NSA
OVER:	Overdrafts. NSA
IRESGB:	Central bank's gross foreign exchange reserves. NSA
IRES-GOLD:	Central bank's international gold reserves. NSA

IRES:	Central bank's gross international reserves. NSA
PROSP-EXP:	Central Bank of the Republic of Turkey's (CBRT) Business Tendency Survey question related to export possibilities (Question 2). NSA
STOCKS-FIN:	Central Bank of the Republic of Turkey's (CBRT) Business Tendency Survey question related to stocks of finished goods (Question 11). NSA
EMP-TEND:	Central Bank of the Republic of Turkey's (CBRT) Business Tendency Survey question related to employment (Question 12). NSA
NEW-ORDERS:	Central Bank of the Republic of Turkey's (CBRT) Business Tendency Survey question related to new orders from the domestic market. (Question 13). NSA

Table A.1. **IP growth: Pseudo out-of-sample forecasting accuracy, 1993:1-2000:12**

Forecast horizon		$h = 3$	$h = 6$	$h = 9$	$h = 12$
Univariate autoregression		Root mean squared forecast error			
		23.2	13.28	10.25	8.56
Bivariate forecasts		MSFE relative to univariate autoregression			
Indicator	Transformation				
greipr	d	1.00	1.03	1.02	0.98
trac	d	1.01	1.08	1.11	1.17
buses	d	0.99	1.03	1.01	1.01
exp	d	0.98	1.10	1.03	0.96
imp	d	1.02	1.19	1.21	1.20
lcpi	d	1.14	1.72	1.67	1.13
lcpi	2d	1.19	1.22	1.11	1.10
lppi	d	1.20	1.19	1.41	1.20
lppi	2d	1.08	1.15	1.05	0.94
lop	d	1.09	0.93	1.02	0.87
lop	2d	1.02	1.00	1.01	1.00
rlop	d	1.09	0.93	1.05	0.88
uscpi	d	1.03	1.04	1.09	1.05
uscpi	2d	1.04	0.99	1.03	0.98
lm1	d	0.89	0.89	1.01	1.02
lm1	2d	1.00	0.95	1.24	0.98
lm2	d	1.11	0.97	0.96	1.10
lm2	2d	1.11	1.01	1.00	1.01
lm2y	d	1.09	1.07	0.99	1.05
lm2y	2d	1.01	1.01	1.00	1.00
lm3	d	1.08	1.02	1.09	1.03
lm3	2d	1.01	1.04	1.01	1.01
lm3y	d	1.10	1.07	1.03	1.10
lm3y	2d	1.01	1.01	0.99	1.00
rlm1	d	0.90	1.05	0.96	1.01
rlm2	d	0.95	1.03	1.09	1.16
rlm2y	d	1.06	1.04	0.97	1.05
rlm3	d	0.97	1.01	1.24	1.16
rlm3y	d	1.04	1.03	1.00	1.04
onir	–	1.13	1.11	0.99	1.10
onir	d	1.25	1.17	0.97	1.08
dr	–	1.24	1.16	1.29	1.37
dr	d	1.18	1.01	1.04	1.02
depo3M	–	1.05	1.05	1.14	1.13
depo3M	d	0.95	0.99	1.00	1.04
traucrate	–	1.42	1.38	1.59	1.53
traucrate	d	1.36	1.06	1.28	1.05
ex-rate	d	1.14	1.06	1.15	1.05
rex-rate	d	1.01	0.98	1.02	1.11
ise100	d	0.92	1.03	1.04	1.02
rise100	d	0.96	1.06	1.06	1.04
divpr	–	1.01	1.03	1.06	0.99
divpr	d	1.10	1.06	1.00	1.03
gold	d	1.09	1.46	1.43	1.19
gold	2d	1.16	1.03	1.07	1.00
rgold	d	1.08	1.32	1.33	1.50
lover	–	1.10	1.18	1.19	1.29
lover	d	1.10	1.12	1.24	1.22
lirescb	–	1.03	1.18	1.38	1.42
lirescb	d	0.93	0.95	0.98	0.99

Table A.1. **IP growth: Pseudo out-of-sample forecasting accuracy, 1993:1-2000:12 (cont.)**

Forecast horizon		$h = 3$	$h = 6$	$h = 9$	$h = 12$
Univariate autoregression		Root mean squared forecast error			
		23.2	13.28	10.25	8.56
Bivariate forecasts		MSFE relative to univariate autoregression			
lires-gold	–	1.32	1.80	2.56	3.19
lires-gold	d	1.09	1.14	1.26	1.28
lires	–	1.05	1.20	1.36	1.32
lires	d	0.97	1.01	1.03	1.02
prosp-exp	–	0.99	1.04	1.02	1.16
stock-fin	–	1.01	1.03	1.07	1.20
emp-tend	–	0.95	1.01	1.05	1.18
new-orders	–	0.87	1.01	0.96	1.04

Note: Bold indicates a relative MSFE < 1.

Table A.2. **IP growth: Pseudo out-of-sample forecasting accuracy, 2001:1-2005:12**

Forecast horizon		$h = 3$	$h = 6$	$h = 9$	$h = 12$
Univariate autoregression		Root mean squared forecast error			
		19.81	12.63	11.12	10.51
Bivariate forecasts		MSFE relative to univariate autoregression			
Indicator	Transformation				
cur	d	1.05	1.03	1.15	1.06
grelpr	d	1.31	1.30	1.07	0.96
trac	d	1.15	1.18	1.21	1.17
buses	d	1.15	1.06	1.00	1.02
exp	d	1.32	1.51	1.11	1.01
imp	d	1.04	1.01	1.05	1.15
inimp	d	1.01	1.14	0.89	1.68
lcpi	d	1.22	1.88	2.11	1.84
lcpi	2d	1.14	1.59	1.30	1.36
lppi	d	1.37	1.75	1.86	1.69
lppi	2d	1.13	1.60	1.23	1.25
lop	d	1.40	1.16	1.09	0.97
lop	2d	1.41	1.02	1.04	1.01
rlop	d	1.52	1.08	1.06	0.97
uscpi	d	1.17	1.22	1.49	1.12
uscpi	2d	0.99	1.01	0.98	1.01
lm1	d	1.19	1.36	1.15	1.11
lm1	2d	1.04	1.15	0.98	1.04
lm2	d	1.52	1.89	2.49	1.90
lm2	2d	1.17	1.01	0.98	1.14
lm2y	d	1.90	3.08	3.05	2.83
lm2y	2d	2.26	2.38	1.95	1.77
lm3	d	1.82	2.29	2.27	1.78
lm3	2d	1.28	1.28	1.31	1.25
lm3y	d	2.03	2.89	3.10	2.60
lm3y	2d	2.19	2.17	1.85	2.11
rlm1	d	0.98	1.00	1.01	1.03
rlm2	d	1.53	1.72	1.93	1.41
rlm2y	d	1.65	1.83	2.42	1.91
rlm3	d	1.95	2.31	2.43	2.63
rlm3y	d	2.31	2.67	3.38	2.73

Table A.2. **IP growth: Pseudo out-of-sample forecasting accuracy, 2001:1-2005:12 (cont.)**

Forecast horizon		$h = 3$	$h = 6$	$h = 9$	$h = 12$
Univariate autoregression		Root mean squared forecast error			
		19.81	12.63	11.12	10.51
Bivariate forecasts		MSFE relative to univariate autoregression			
onir	–	7.14	18.26	6.27	7.00
onir	d	7.15	5.12	2.24	9.10
dr	–	1.06	0.95	1.20	1.15
dr	d	1.04	1.03	1.03	1.09
depo3M	–	1.13	2.82	3.52	2.58
depo3M	d	1.31	3.85	2.64	2.64
traucrate	–	1.41	1.62	1.64	1.44
traucrate	d	0.83	0.98	0.71	0.68
ex-rate	d	2.70	3.05	4.21	4.31
rex-rate	d	3.50	3.77	4.07	5.66
ise100	d	1.10	1.00	1.08	0.52
rise100	d	0.94	1.09	1.07	0.65
divpr	–	1.22	1.84	2.12	2.08
divpr	d	4.38	7.03	6.74	2.70
irspread	–	1.99	2.15	2.88	2.76
irspread	d	1.47	0.99	1.19	1.52
gold	d	0.98	0.86	1.50	1.16
gold	2d	1.02	1.01	1.06	0.86
rgold	d	0.98	0.90	1.06	0.89
lover	–	1.07	1.12	1.25	1.26
lover	d	1.10	1.00	1.05	0.98
lirescb	–	1.95	1.38	1.54	1.96
lirescb	d	1.93	1.20	1.01	1.19
lires-gold	–	1.15	1.25	1.45	1.31
lires-gold	d	1.19	1.23	0.94	0.99
lires	–	1.27	1.48	1.61	2.02
lires	d	1.16	1.11	0.98	1.02
prosp-exp	–	1.18	0.83	0.79	1.11
stock-fin	–	1.00	0.94	0.97	1.01
emp-tend	–	0.93	0.98	0.96	1.08
new-orders	–	1.17	0.98	0.87	1.12

Note: Bold indicates a relative MSFE < 1.

Table A.3. **CPI inflation: Pseudo out-of-sample forecasting accuracy, 1993:1-2000:12**

Forecast Horizon		$h = 3$	$h = 6$	$h = 9$	$h = 12$
		Root Mean Squared Forecast Error			
Univariate Autoregression		23.63	21.16	23.67	21.66
Bivariate Forecasts		MSFE Relative to Univariate Autoregression			
Indicator	Transformation				
lipi	d	1.04	1.03	1.04	1.06
lipi	2d	1.01	1.01	1.02	1.02
hp-ipi	–	1.05	1.05	0.96	1.05
grelpr	d	1.01	1.00	1.01	1.01
trac	d	1.01	1.00	0.99	1.00
buses	d	1.23	1.38	1.22	1.24
exp	d	1.07	0.80	0.70	0.72
imp	d	0.96	1.14	1.05	1.07
lppi	d	0.91	0.85	0.57	0.84
lppi	2d	1.06	0.89	0.70	0.83
lop	d	1.01	1.01	0.99	1.01
lop	2d	1.02	0.99	0.91	0.96
rlop	d	1.01	1.01	1.00	1.01
uscpi	d	1.02	1.00	1.01	1.01
uscpi	2d	0.99	0.99	0.99	0.99
lm1	d	1.15	1.01	1.00	1.02
lm1	2d	1.15	1.05	0.99	1.04
lm2	d	1.17	1.21	1.12	1.06
lm2	2d	1.30	1.47	1.13	1.02
lm2y	d	1.13	0.99	0.93	1.01
lm2y	2d	1.01	0.98	0.98	1.00
lm3	d	1.06	2.01	1.57	1.07
lm3	2d	1.14	2.10	1.51	1.04
lm3y	d	1.16	1.00	0.96	1.03
lm3y	2d	1.05	0.99	0.98	1.02
rlm1	d	0.94	0.85	0.81	0.83
rlm2	d	0.96	0.97	0.95	0.77
rlm2y	d	0.99	0.74	0.91	0.74
rlm3	d	0.92	0.97	0.81	0.78
rlm3y	d	0.92	0.76	0.76	0.77
onir	–	2.02	1.33	1.43	1.39
onir	d	1.28	1.05	1.01	1.08
dr	–	1.15	1.03	1.01	1.00
dr	d	1.12	0.98	0.83	0.89
depo3M	–	1.41	1.18	1.09	1.10
depo3M	d	1.14	1.03	1.06	0.97
traucrate	–	2.65	1.57	1.27	1.85
traucrate	d	2.08	1.31	1.19	1.42
ex-rate	d	1.69	1.17	1.42	1.04
rex-rate	–	1.69	1.46	1.41	1.23
ise100	d	1.05	1.00	1.05	1.01
rise100	d	1.08	1.02	0.95	1.00
div-pr	–	1.01	0.99	1.01	0.92
div-pr	d	1.18	1.06	0.99	0.97
gold	d	1.04	1.19	1.08	1.11
gold	2d	1.03	1.01	0.99	1.01
rgold	d	1.02	1.32	1.22	1.08
lover	–	1.06	0.97	0.90	0.93
lover	d	0.99	1.04	1.04	1.05
lirescb	–	1.43	1.49	1.45	1.76

Table A.3. **CPI inflation: Pseudo out-of-sample forecasting accuracy, 1993:1-2000:12 (cont.)**

Forecast Horizon		$h = 3$	$h = 6$	$h = 9$	$h = 12$
Univariate Autoregression		Root Mean Squared Forecast Error			
		23.63	21.16	23.67	21.66
Bivariate Forecasts		MSFE Relative to Univariate Autoregression			
lirescb	d	1.05	1.04	1.00	1.03
lires-gold	–	1.12	1.03	0.99	0.99
lires-gold	d	1.17	1.02	0.95	0.99
lires	–	1.16	1.24	1.12	1.51
lires	d	0.99	0.99	1.00	1.01
prosp-exp	–	1.16	0.74	0.77	0.83
stock-fin	–	0.97	0.78	0.61	0.73
emp-tend	–	1.03	0.74	0.63	0.66
new-orders	–	1.08	0.69	0.64	0.53

Note: Bold indicates a relative MSFE < 1.

Table A.4. **CPI inflation: Pseudo out-of-sample forecasting accuracy, 2001:1-2005:12**

Forecast horizon		$h = 3$	$h = 6$	$h = 9$	$h = 12$
Univariate autoregression		Root mean squared forecast error			
		15.2	13.12	13.31	13.65
Bivariate forecasts		MSFE relative to univariate autoregression			
Indicator	Transformation				
lipi	d	1.05	1.02	0.98	1.00
lipi	2d	1.02	1.00	1.00	0.98
hp-ipi	–	1.04	1.09	1.12	1.11
cur	d	1.09	1.00	0.99	0.99
grelpr	d	1.02	1.03	0.99	1.00
trac	d	1.10	1.06	1.24	1.28
buses	d	1.16	1.00	1.06	1.16
exp	d	1.28	1.23	0.96	1.03
imp	d	1.13	1.00	0.89	1.01
inimp	d	1.11	1.03	1.10	1.11
lppi	d	1.15	1.11	1.45	1.52
lppi	2d	1.03	1.03	1.09	1.04
lop	d	1.13	1.05	0.99	1.08
lop	2d	1.01	1.02	0.98	1.00
rlop	d	1.04	1.05	0.99	1.07
uscpi	d	1.26	1.05	0.98	0.66
uscpi	2d	1.12	1.02	0.96	1.01
lm1	d	1.01	1.12	1.19	1.18
lm1	2d	1.16	1.07	1.00	1.01
lm2	d	0.98	1.25	1.75	1.52
lm2	2d	0.95	1.00	0.91	0.97
lm2y	d	1.23	0.99	0.92	1.12
lm2y	2d	0.90	0.94	0.88	0.95
lm3	d	0.96	0.97	1.16	1.06
lm3	2d	0.98	0.98	0.96	1.02
lm3y	d	1.42	0.98	1.00	1.10
lm3y	2d	0.98	0.96	0.98	0.96
rlm1	d	1.02	1.01	1.39	1.13
rlm2	d	0.94	0.90	0.97	0.94
rlm2y	d	0.93	0.92	0.91	1.04
rlm3	d	1.03	0.95	0.90	0.96
rlm3y	d	0.90	0.94	0.91	1.03

Table A.4. **CPI inflation: Pseudo out-of-sample forecasting accuracy, 2001:1-2005:12 (cont.)**

Forecast horizon		$h = 3$	$h = 6$	$h = 9$	$h = 12$
Univariate autoregression		Root mean squared forecast error			
		15.2	13.12	13.31	13.65
Bivariate forecasts		MSFE relative to univariate autoregression			
onir	–	1.72	0.96	0.98	1.11
onir	d	2.35	1.04	1.01	1.23
dr	–	0.96	0.95	1.09	1.42
dr	d	1.07	0.98	0.90	1.03
depo3M	–	2.02	1.57	1.41	1.28
depo3M	d	1.77	1.64	1.51	1.30
traucrate	–	1.37	1.28	1.47	1.77
traucrate	d	1.02	0.90	1.18	0.97
ex-rate	d	1.88	1.53	1.21	1.46
rex-rate	–	1.31	2.16	2.53	3.62
ise100	d	1.16	1.00	0.96	1.00
rise100	d	1.11	1.00	0.90	0.99
divpr	–	1.03	1.15	1.74	1.89
divpr	d	2.43	3.51	6.54	6.59
irspread	–	1.25	1.18	1.41	1.37
irspread	d	1.07	1.09	1.20	1.35
gold	d	1.20	0.94	0.99	1.40
gold	2d	1.34	1.05	0.88	0.92
rgold	d	1.30	0.92	1.02	1.51
lover	–	1.03	1.23	1.39	1.46
lover	d	1.09	1.01	1.02	1.09
lirescb	–	1.03	1.33	1.50	1.61
lirescb	d	1.12	1.16	0.95	1.17
lires-gold	–	1.00	1.31	1.54	2.07
lires-gold	d	1.04	1.29	1.53	1.95
lires	–	1.30	1.59	1.84	1.86
lires	d	1.12	1.36	1.49	1.36
prosp-exp	–	1.10	0.96	1.29	1.49
stock-fin	–	1.13	1.24	1.33	2.13
emp-tend	–	1.11	0.97	1.00	1.25
new-orders	–	1.38	1.18	1.25	1.24

Note: Bold indicates a relative MSFE < 1.

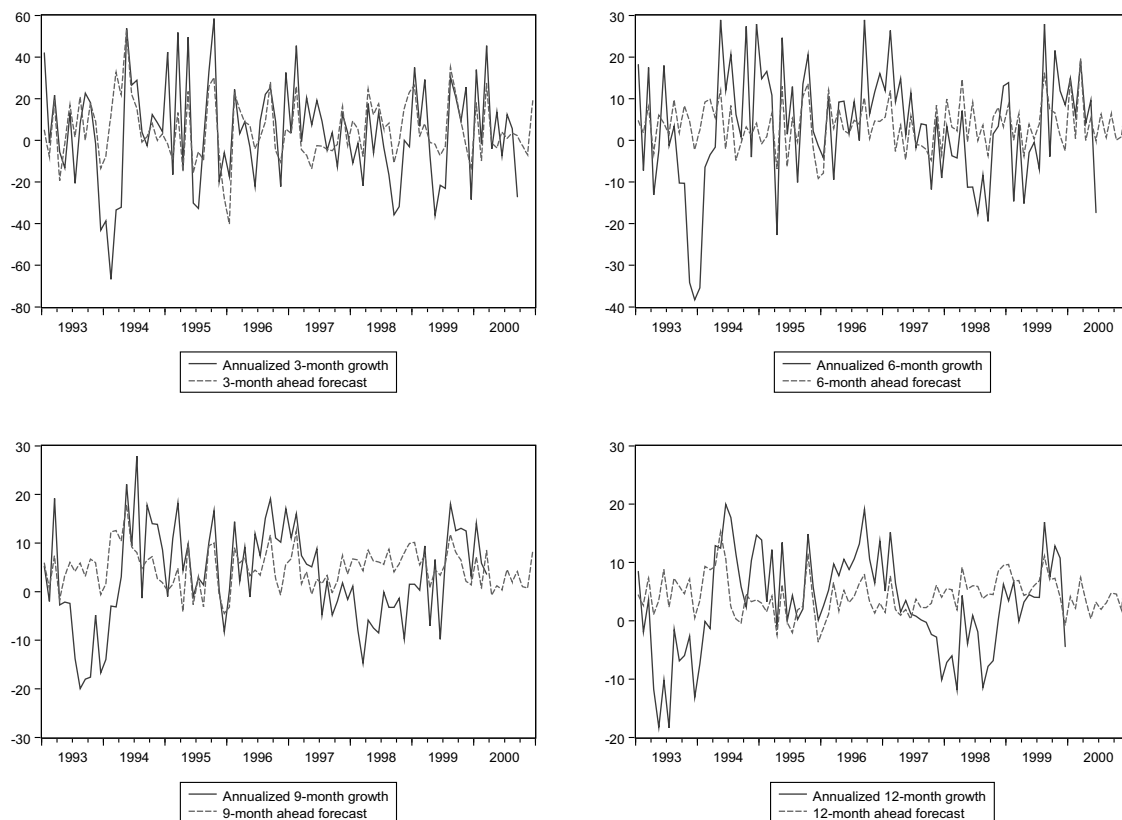
Figure A.1. **IP growth, 1993:1-2000:12**

Figure A.2. **IP growth, 2001:1-2005:12**

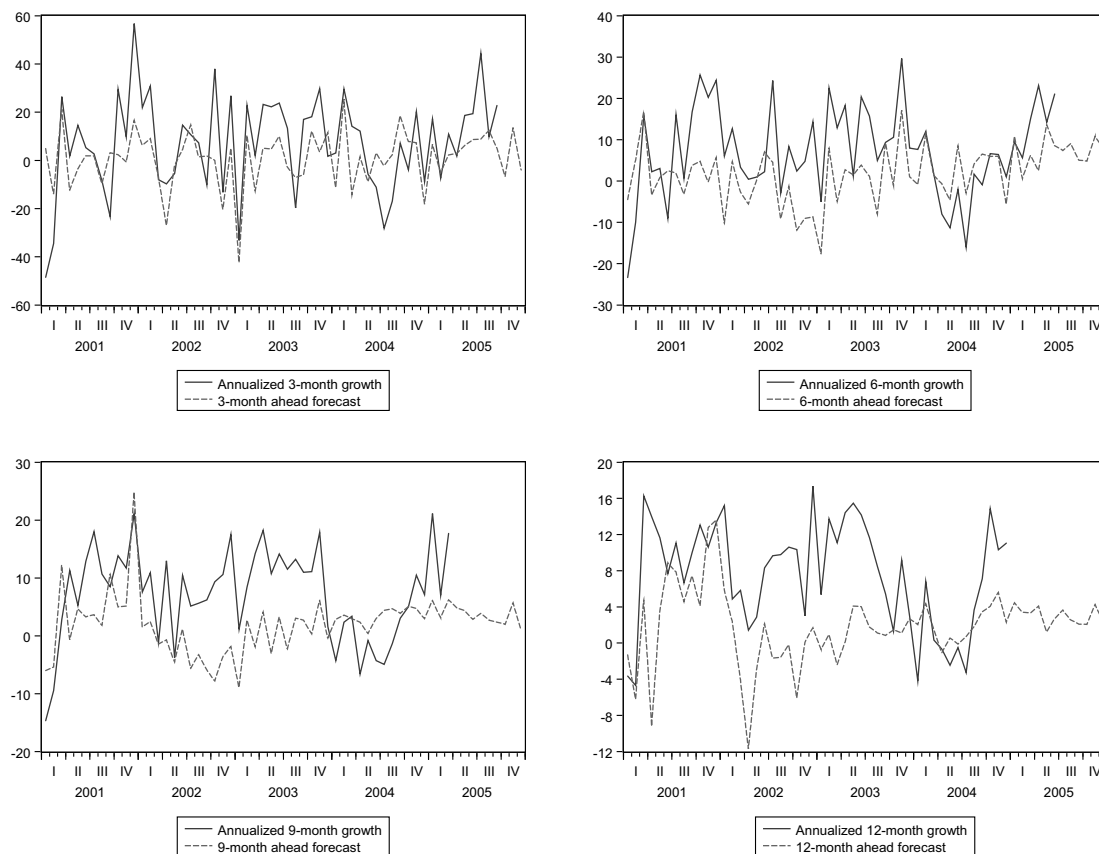


Figure A.3. **Changes in CPI inflation, 1993:1-2000:12**

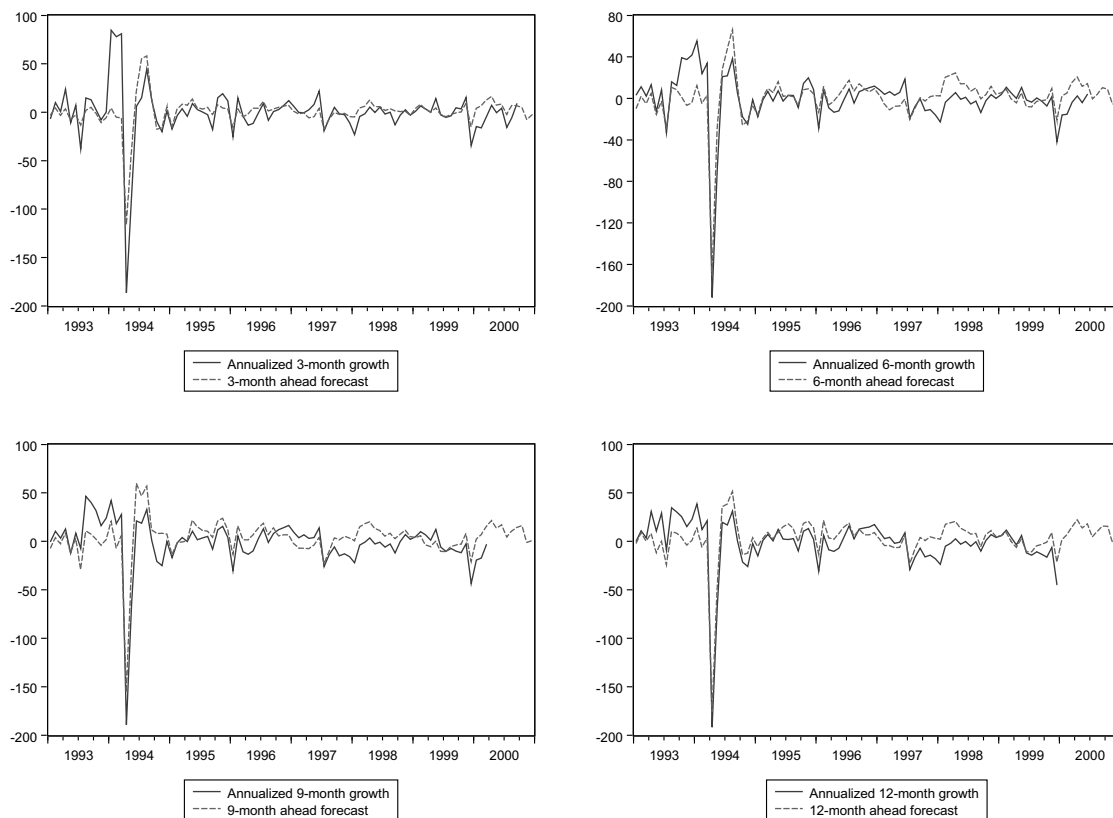
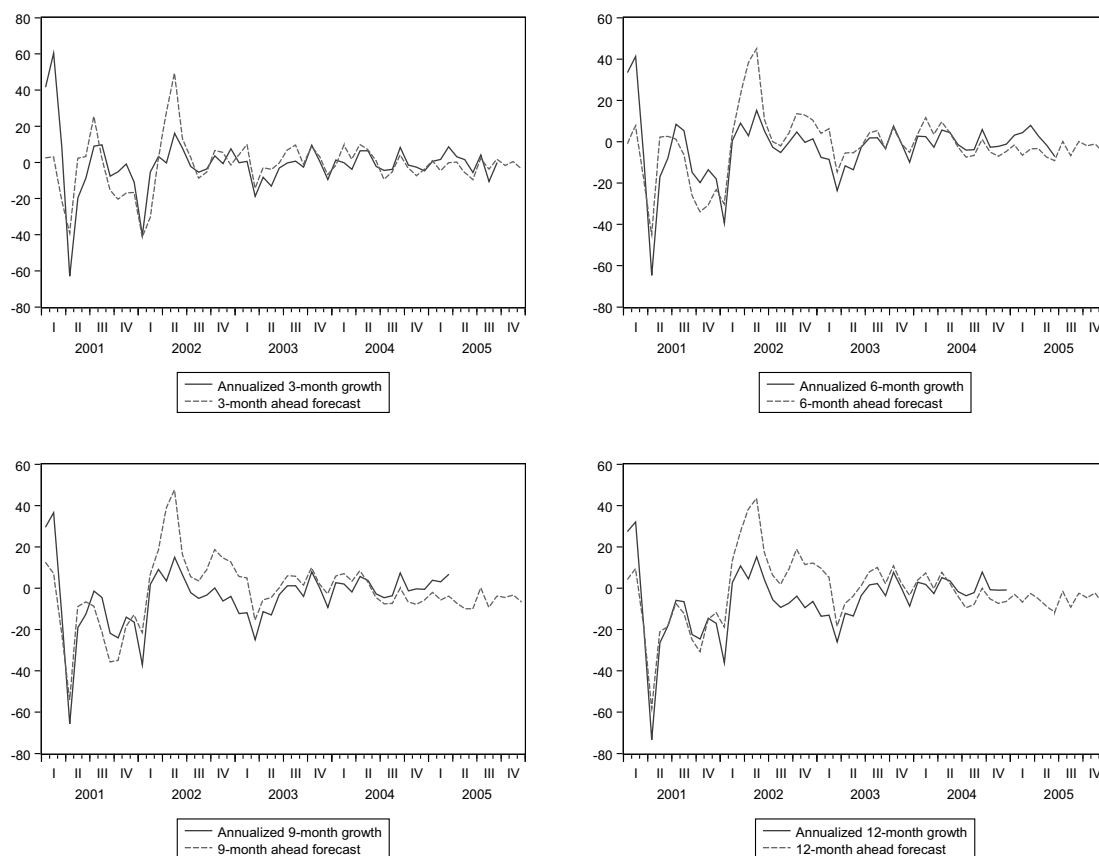


Figure A.4. **Changes in CPI inflation, 2001:1-2005:12**



Making leading indicators more leading: A wavelet-based method for the construction of composite leading indexes

by
Marco Gallegati*

This paper proposes a novel wavelet-based approach for constructing composite indicators. The wavelet-based methodology exploits the ability of wavelet analysis to analyse the relationships between variables on a scale-by-scale, rather than aggregate, basis. A wavelet-based index which combines several scale-based sub-indexes is constructed by using a scale-by-scale selection of the components included in the OECD composite leading indicator (CLI) for the US. The comparison with the CLI and its derived measures indicate that the wavelet-based composite index tends to provide early signals of business cycle turning points well in advance of the OECD CLI. Moreover we find that the reliability of the signals tends to increase considerably when the sub-index obtained from the time scale components corresponding to minor cycles, that is, 2-4 years, is removed from the overall wavelet-based index.

Keywords: wavelets; composite leading indicators; early warning signals

JEL classification: C1; C3; C5; E3

* Polytechnic University of Marche, Faculty of Economics, Piazzale Martelli, 8, 60121 Ancona, Italy. marco.gallegati@univpm.it I would like to thank James B. Ramsey for his invaluable guidance, inspiration and continuous encouragement while developing this research proposal. I would also like to thank two anonymous referees for providing many useful comments and suggestions. All remaining errors are, of course, mine.

1. Introduction

Composite indicators are summary measures, widely used in social science research, that combine a set of individual indicators exhibiting common patterns with respect to complex unobservable phenomena, such as the current economic situation or the overall level of financial conditions.¹ Index methods provide an interesting alternative to forecasting models based on economic theory because of their ability to summarise the huge information that is actually available to researchers because of the increasing availability of large data sets. Developments and research activity in the area of composite indicators mainly relates to the selection and revision of component series, for example, OECD (2002, 2007) and Levanon et al. (2011), with changes to methodology representing rare exceptions, as in the case of the diffusion index method by Stock and Watson (2002).²

Following the modern approach to business cycles (Lucas, 1977) based on the growth cycles definition as periods of cyclical upswings and downswings around an underlying trend,³ spectral filtering methods have become common processing tools in economics. In particular, band-pass (approximate) filters, such as the Baxter-King (1999) and Christiano-Fitzgerald (2003) filters, have been widely used in business cycles analysis to extract the cyclical component corresponding to fluctuations in the 1.5 to 8(10) years frequency band. The same goal may be pursued by the wavelet methodology since there is a correspondence between the filtered cyclical components and the time scale components of wavelet analysis because of the inverse relationship between time scale and frequency.

In this paper a new approach is presented in which the component series of composite indicators are selected by exploiting information in the time domain as well as in the frequency domain by means of wavelet analysis. The proposed methodology consists in constructing an overall composite index obtained by aggregating several scale-based sub-indexes corresponding to different business cycles frequency bands, where component series are selected on the basis of their statistical performance at each time scale. The result is a composite indicator that, by efficiently use all available information, can potentially reduce the number of false signals, while attaining parsimony.

The proposed methodology is applied to the OECD composite leading indicator for the United States, since the OECD system of leading indicators is based on the growth cycle approach. Specifically, after decomposing each individual component series of the CLI into its time scale components, we select at each time scale those individual indicators that display the best overall statistical performance to construct the corresponding scale-based sub-index. Then the scale-based sub-indexes corresponding to business cycles frequency bands are aggregated to obtain the overall wavelet-based composite leading indicator.

We evaluate the performance of the wavelet-based composite leading indicator as to the CLI and its derived measures, the 6-month and 12-month rate of change, in terms of length and consistency of the lead time at turning points, and number of missing or extra signals. The results indicate that the wavelet-based composite leading indicator gives early reliable signals of recessions with a longer lead relative to CLI, six months, and its derived

measures. In particular, a three month extra lead time relative to the six month CLI rate of change is in evidence. Moreover, we find that the performance of the wavelet-based composite leading indicator considerably improves in terms of its reliability to provide early signals of approaching turning points and the number of extra signals with respect to OECD reference chronology, when the sub-index obtained from the time scale components corresponding to minor cycles, that is, 2-4 years, is removed.

The paper is organised as follows. Section 2 describes the motivation for using wavelets in the indicators approach and the methodology to obtain a wavelet-based composite index. Section 3 explains the construction of the wavelet-based composite leading indicator for the US and in Section 4 we evaluate its performance relative to the OECD CLI and its derived measures. Section 5 concludes.

2. Wavelet-based composite indexes: Motivation and methodology

In the non-parametric indicators approach⁴ to the construction of composite indexes the attention of the researcher is focussed on finding the best-performing indicators with respect to the phenomenon to be explained (turning points, crisis, stress periods, etc.).⁵ This search process relies on application of conventional time domain methods and tools where the timing classification and selection of reliable individual indicators is based on the time domain information content provided by time series aggregate data.⁶ The assumption underlying the procedure of selection of these reliable individual indicators is that the remaining part of information, obtainable by analysing the data in the frequency domain, is not relevant. Thus, the process of revision of composite indexes is generally limited to their composition with the reliability of individual indicators over time regularly tested by checking whether their timing pattern changes or weakens.

However, if the variable realisations depend on different frequency components rather than just one, as it is implicitly stated in the standard time domain approach, any information regarding the different frequency components contained into the original data series will be lost (Masset, 2008).⁷ That economic (and financial) relationships can differ across frequencies was first documented by Engle (1974, 1978) using band spectrum regressions, and more recently by Ashley and Verbrugge (2009) using the frequency dependence approach. In such a context, joint time-frequency analysis methods combining information from both time-domain and frequency-domain simultaneously, like wavelets, can be very appealing.

Wavelets are mathematical functions that, although widely used in many other disciplines such as geophysics, climatology and acoustics, remain relatively unknown to practitioners in the fields of economics and finance. They allow the decomposition of a signal into its different frequency components to study the dynamics of each of these components separately.⁸ In particular, the analysis in the time-frequency domain is able to produce more accurate information on the presence of (highly localised) patterns, possibly only at certain scales, and dominant scales of variation in the data, like characteristic scales, as well as on the relationships between variables (see Ramsey and Lampart, 1998a, 1998b; Kim and In, 2003; Aguiar-Conraria et al., 2008; Aguiar-Conraria and Soares, 2011; Gallegati et al., 2011).

The most important gain from using the multi-resolution decomposition properties of wavelet transform for the indicators approach is that it allows to efficiently process all available information by exploiting the different informative content of individual

indicators at different time scales. Separating these scales can reveal patterns and features in the data beyond those evidenced from the usual aggregate perspective and may be useful in analysing situations in which the degree of association between two time series is likely to change across frequency bands.⁹ Indeed, the time scale decomposition property of wavelets allows identification of different relationships between variables on a scale-by-scale basis so that it is possible to separate those time scales at which the relationship is statistically significant from those scales at which it is not.

The methodology proposed in this paper differs from the traditional indicators approach as to the construction and variable selection procedures in that the overall composite index is obtained by aggregating several sub-indices, each corresponding to a different frequency band.¹⁰ In particular, each sub-index is obtained by combining those indicators displaying the best statistical cross-correlations performance on a scale-by-scale basis. The result is a composite indicator that, by combining the best-performing individual components at each scale, is able to process all available information efficiently and parsimoniously. Moreover, since the wavelet transform allows the decomposition of the observed time series into a sum of structural and random error components, through scale selection it can also deal with the problem of false signals by reducing the incidence of irregular (erratic) movements.

Let $I_1, I_2, \dots, I_N$ be the set of N reliable indicators available for the construction of the composite index. By applying a J -level multi resolution decomposition analysis we can provide a complete decomposition of each individual indicator I_i into a smoothed version of the original signal and a set of detail information at different scales:

$$I_i \approx S_j[I_i] + D_j[I_i] + \dots + D_j[I_i] + \dots + D_2[I_i] + D_1[I_i] \quad (1)$$

where $S_j[I_i]$ contains the smooth component of the signal, and $D_j[I_i]$, with $j = 1, 2, \dots, J$, the detail signal components, with increases in j corresponding to a coarser resolution, or lower frequency band. For each level of decomposition $j = 1, 2, \dots, J$ we can construct a scale-based composite sub-index CI_{D_j} by a weighted aggregation of the subset $k \leq n$ statistically significant indicators at that scale,

$$CI_{D_j} = \omega_{1,j}D_j[I_1] + \omega_{2,j}D_j[I_2] + \omega_{3,j}D_j[I_3] + \dots + \omega_{k,j}D_j[I_k] \quad (2)$$

where ω_{ij} is the weight of each indicator i at scale j . Weights are determined through the equal variance method (see Cardarelli et al.) so that each component contribution is first adjusted for the inverse of its standard deviation (its relative amplitude) and then normalised so that the components' weights sum to one. Finally, by aggregating the j scale-based composite sub-indexes CI_{D_j} we can obtain the wavelet-based composite index CI^w , that is

$$CI^w = CI_{S_j} + CI_{D_j} + \dots + CI_{D_j} + \dots + CI_{D_1} \quad (3)$$

Two main features of the wavelet-based composite index CI^w are noteworthy: parsimony and degree of smoothness. The first is related to the fact that at each time scale j just a subset, sometimes a small subset, of all reliable indicators are likely to have the properties required in order to be included in the corresponding composite sub-index CI_{D_j} . The latter means that since the noise component is generally restricted to the lowest scales

$j = 1, 2$ (for example, Ramsey et al., 2010; Gallegati and Ramsey, 2012) and the relationships between variables at the lowest scales are generally statistically not significant (for example, Gallegati et al., 2009, 2011; Gallegati and Ramsey, 2013), the sub-indexes corresponding to these scales can be potentially excluded from the overall composite index without a significative loss of information. As a result, a wavelet-based composite index, by excluding redundant information and highly irregular components, can be expected to improve its performance relative to its analogue time domain composite index because of its ability to reduce the risk of providing false signal.

3. An application of the wavelet-based approach to composite indicators: The OECD CLI for the US

Within a system of cyclical indicators, leading indicators are definitely those ones attracting most of the attention at any level (economists, businesses, professional forecasters, and policymakers) because of their ability to provide early signals about future economic conditions. By exploiting the different informative content of individual indicators at different time scales, wavelet analysis allows to examine whether the degree of association between two time series differ across different frequency bands. In particular, the identification at each time scale of those components that, according to purely statistical grounds, display the best performance as leading indicators of future turning points in economic activity enables the construction of a composite leading indicator with longer leading properties.¹¹

Hence, in this section, in order to assess the usefulness of the proposed methodology, we construct a composite leading indicator with longer leading properties for the US and compare it with the OECD composite leading indicator (CLI from now on).

3.1. Scale-by-scale evaluation of CLI component series for the US

In order to emphasise the differences between the wavelet-based and the traditional methodology for constructing composite indexes we use the same component series currently included in the OECD CLI (OECD, 2002). The set of component series for the US CLI is given by the following variables: the dwelling started (number), the consumer sentiment indicator from the University of Michigan (normal=100), the share prices index from the New York Stock Exchange common stocks (1995=100), the net new orders for durable goods (constant USD million, 1996), the spread of interest rates as the difference between the 10-year treasury bonds and the Federal funds (per cent per annum), the average weekly number of hours of work in manufacturing sector, and the Purchasing Manager Diffusion Index (percentage of balance).

Since the OECD system of composite leading indicators is based on the growth cycle approach,¹² identification of the business cycle component is obtained by applying a filtering to the component series so as to extract the cyclical component corresponding to fluctuations in the 1.5 to 8(10) years frequency band. The same goal may be pursued by using wavelet analysis. Indeed, the time-frequency decomposition provided by the (discrete) wavelet transform decomposes a time series into different time scales, each associated to a specific frequency band.¹³ Specifically, as shown in Table 1, where the frequency resolution interpretation of wavelet decomposition scale levels for a 6-level decomposition and monthly data is reported, we have that:

- detail levels D_1 , D_2 and D_3 , represent the very short-run dynamics of a signal (and contains most of the noise of the signal),
- detail levels from D_4 to D_6 captures fluctuations within the 16-128 months frequency range (corresponding to business cycle frequency band),
- the smooth component S_6 (not shown in Table 1) captures oscillations with a period longer than 12 years which correspond to the low-frequency components of a signal.

From the frequency interpretation of wavelet detail levels provided in Table 1 follows that detail level components D_4 , D_5 and D_6 roughly correspond to conventional periodicities used in the modern definition of business cycles (Stock and Watson, 1999). Hence, in what follows we restrict our analysis to these components because the frequency range we are interested in for business cycle analysis is between 1.5 and 8(10) years.

Table 1. **Frequency interpretation of MRD scale levels**

Scale level (j)	Detail level (D_j)	Monthly frequency resolution
1	D_1	2-4
2	D_2	4-8
3	D_3	8-16
4	D_4	16-32
5	D_5	32-64
6	D_6	64-128

Note: Since the level of the transform defines the effective scale λ_j of the corresponding wavelet coefficients, for all families of Daubechies compactly supported wavelets the level j wavelet coefficients are associated with changes at scale 2^{j-1} . Since scale 2^{j-1} corresponds to frequencies in the interval $f \in [1 / 2^{j+1}, 1 / 2^j]$, using monthly data scale 1 wavelet coefficients are associated to 2-4 month periods, while scales 2 to 6 are associated to 4-8, 8-16, 16-32, 32-64 and 64-128 month periods, respectively.

In order to construct a wavelet-based composite leading indicator we first need to decompose each individual indicator into its time scale components and then examine their relationships with the reference series on a scale-by-scale basis. Hence, we transform each component series of the CLI to month-to-month changes using the symmetric per cent change formula, except for interest rate spread where simple arithmetic differences are calculated, and decompose the growth rate of each component indicator into its time scale components by applying the maximal overlap discrete wavelet transform, MODWT, with the Daubechies (1992) least asymmetric (LA) wavelet filter of length $L = 8$, since this is the most widely used filter in economic applications.¹⁴

Then, we examine the relationships of each component series with the industrial production index at different time scales. The OECD system of composite leading indicators has used the index of industrial production as a reference series because it is available on a monthly basis (whereas GDP data are only available on a quarterly basis) and, as documented by previous OECD studies (for example, Nilsson, 1987; OECD, 2012), the cyclical profiles of the industrial production index and GDP are very closely related.¹⁵ In addition, regarding the reference chronology, that is, the historical cyclical pattern, the turning points detected in the industrial production index coincide well with those of GDP for most OECD countries, especially the US (OECD, 2002).

The selection of individual indicators at each scale level is based on the cyclical performance of each component series evaluated according to the results of cross-correlation analysis on a scale-by-scale basis.¹⁶ In order to identify at any time scale which

variables have better leading indicators properties for economic activity we use the correlation value at the peak and the location of the peak of the cross correlation function, since they both provide useful criteria for selecting candidate indicators. A high cross-correlation of the cyclical behaviour indicates that the potential component series leads the reference series over the whole cycle, not only at turning points, and the location of the peak provides a reliable alternative indicator of the average lead time.

The results from the analysis of the cross-correlation function on a scale-by-scale basis between each component and the industrial production index may be summarised as follows:

- at scales corresponding to the business cycle frequency range, that is scales 4, 5 and 6, differences in the strength and timing of the leading relationships across time scales are in evidence for each variable;
- at scales outside the business cycle frequency range, that is scales 1, 2 and 3, there is almost no evidence of any leading behaviour since the magnitude of the association between variables is generally close to zero at all leads (rare exceptions only at scale 3);
- as to the average lead time of the various individual indicators at different scales some indicators are classifiable as longer-leading (University of Michigan Index of Consumer Sentiment, Purchasing Manager Diffusion Index and number of dwelling started) and others as shorter leading (share prices index and average weekly hours manufacturing);¹⁷
- the average lead time tends to increase as the time scale increases, from 2 periods at scale 4 to 12 periods at scale 6 (see Gallegati, 2008, for similar results between stock returns and aggregate activity).

Any individual component whose leading correlation at peak is above the average value calculated over all components is included in the corresponding sub-index with weights since the correlation values at the peak are all highly significant. Indeed, the correlation values of the included components tend to increase as the scale increases, ranging from 0.56 for the number of dwellings started at scale 4 to 0.87 for the Purchasing Manager Diffusion Index at scale 6. The individual components selected from cross-correlation analysis that make up the leading sub-indexes, CLI_{D_6} , CLI_{D_5} and CLI_{D_4} , are listed in Table 2. The average lead time of the indicator over the industrial production index and the closeness of fit are presented in columns 2 and 3, measured, respectively, by the lead at which highest correlation occurs and the value of the correlation coefficient at the highest peak. Finally, in column 4 it is shown the standardisation factor of each indicator in each sub-index determined according to the equal variance weight method.

In Figure 1 it is shown the wavelet-based composite leading index, CLI^W , obtained by summing up the scale-based composite sub-indexes

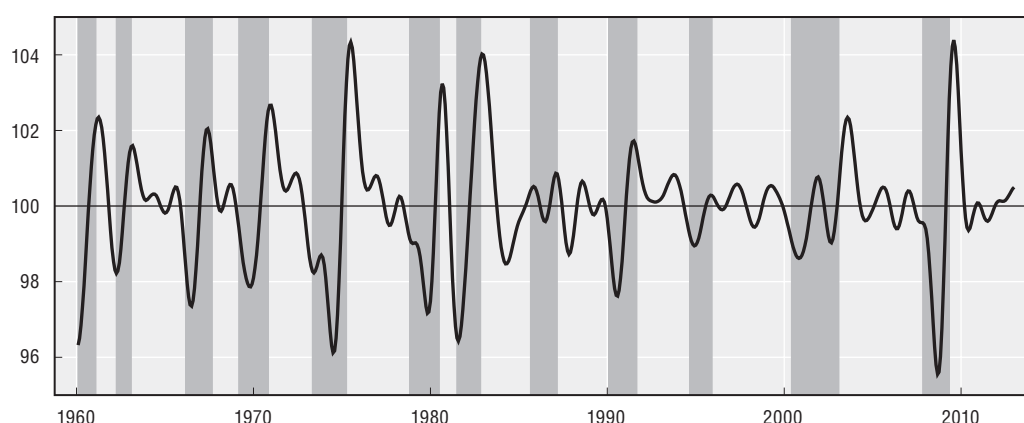
$$CLI^W = CLI_{D_6} + CLI_{D_5} + CLI_{D_4}. \quad (4)$$

Table 2. **Components of the sub-indexes CLI_{D_3} , CLI_{D_5} and CLI_{D_6} of the wavelet-based composite leading indicator with their scale-by-scale standardisation factors**

CLI_{D_4} components	Lead	R^2	Stdz. factors
Purchasing Manager Diffusion Index	-3	0.8440	0.2713
Number of dwelling started	-4	0.6120	0.3114
Stock prices, 500 common stocks	-5	0.6244	0.4173
CLI_{D_5} components			
University of Michigan Index of Consumer Sentiment	-9	0.7017	0.3189
Purchasing Manager Diffusion Index	-6	0.8578	0.2116
Number of dwelling started	-9	0.6966	0.2175
Stock prices, 500 common stocks	-7	0.6806	0.2520
CLI_{D_6} components			
University of Michigan Index of Consumer Sentiment	-17	0.7177	0.4518
Purchasing Manager Diffusion Index	-13	0.7718	0.3730
Number of dwelling started	-11	0.7759	0.1752

Note: Lead and R^2 refer to the lead time and the value of the maximum cross-correlation between each component and the index of industrial production. Stdz. Factors refers to the weight for each component in each sub-index.

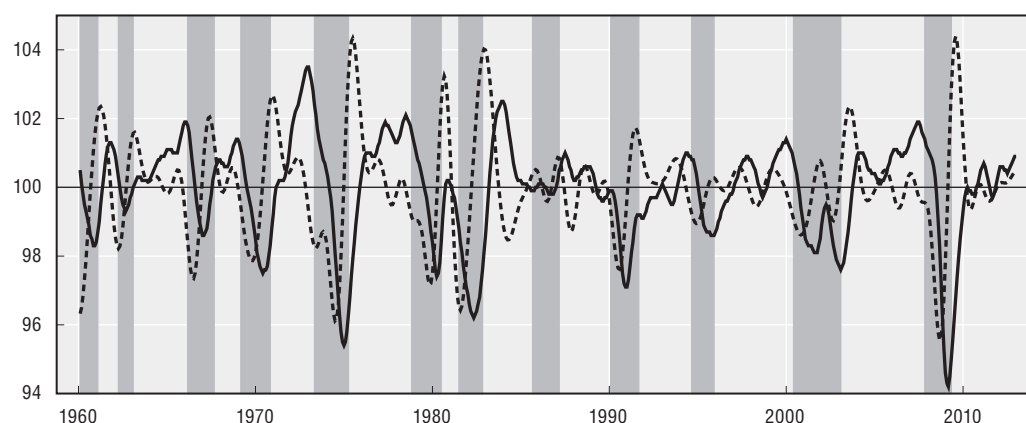
Figure 1. **Wavelet-based compose leading indicator CLI^W**



Note: Growth cycle downswings (measured from peak to trough) in the modified OECD chronology are represented by grey shaded areas.

4. Evaluating the historical performance of CLI^W

Since the wavelet-based composite leading indicator CLI^W is constructed from the same underlying set of seven leading indicator variables used for OECD CLI, in this section we compare the ability of the wavelet-based composite leading indicator CLI^W to provide early signals of turning points in economic activity relative to the amplitude adjusted CLI.¹⁸ In particular, we compare the historical performance the two leading indicators, where the datasets are complete. The reason is that the aim of the paper is to evaluate the potential contribution coming from the new approach in order to make leading indicators more leading. Indeed, the comparison of the historical estimates is generally adopted as a first step also in the revision process of individual components periodically carried out (for example, OECD, 2002; Levanon et al., 2011).

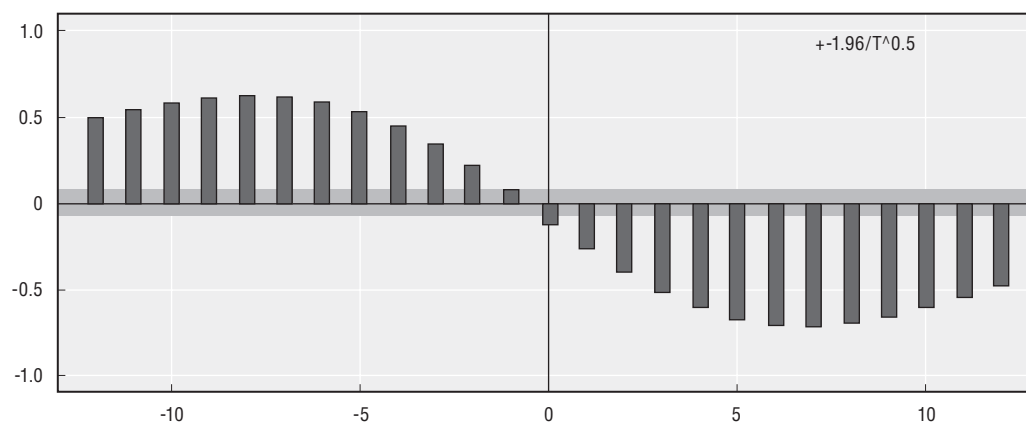
Figure 2. **OECD-CLI and CLI^W** 

Note: Full line = OECD-CLI; dotted line = CLI^W . Growth cycle downswings (measured from peak to trough) in the modified OECD chronology, are represented by grey shaded areas.

4.1. CLI^W vs the amplitude adjusted CLI

In Figure 2 the CLI^W is shown along with the amplitude adjusted CLI. The graphical examination of the two composite leading indicators clearly indicates that movements of the CLI^W tend to precede quite regularly those of the amplitude adjusted CLI.

The visual evidence presented in Figure 2 is confirmed by the cross-correlation analysis between CLI^W and CLI displayed in Figure 3. The location of the peak of the cross-correlation function suggests a leading relationship of CLI^W relative to the CLI, with an average leading time for the CLI^W of about nine months, while its coefficient value at the peak indicates that the cyclical profiles of the two leading indicators are correlated.

Figure 3. **Cross-correlation between CLI^W at $t + i$ and CLI at t .**

A complement to cross-correlation analysis in order to evaluate the performance of the two indicators is provided by the peak-and-trough analysis¹⁹ presented in Table 3, which examines the homogeneity of leads, in terms of length and consistency of the leading times, at turning points, rather than over the whole sample period. The application of peak-and-trough analysis requires to determine a chronology for the cyclical turning points of the reference series. We adopt the OECD chronology, where only major cycles are

Table 3. **Peak-and-trough analysis of the CLI^W and CLI**
Leads in months of CLI^W and CLI at peaks and troughs

Peaks	CLI	CLI^W	Diff.	Troughs	CLI	CLI^W	Diff.
				1961:02	-3	-12	9
1962:04	-5	-12	7	1963:02	-5	-10	5
1966:03	-1	-36	35	1967:09	-7	-15	8
1969:03	-2	-21	19	1970:11	-5	-13	8
1973:05	-4	-28	24	1975:04	-3	-9	6
1978:11	-4	-40	36	1980:07	-4	-9	5
1981:07	-5	-8	3	1982:11	-6	-15	9
1985:10	-21	-33	12	1987:03	-4	-8	4
1990:02	-14	-18	4	1991:09	-8	-14	6
1994:09	-3	-38	35	1995:12	-1	-11	10
2000:06	-5	-39	34	2003:02	0	-6	6
2007:11	-4	-51	47	2009:05	-2	-8	6
Mean	-6.2	-29.5	23.3	Mean	-4.0	-10.8	6.8
Median	-4.0	-33.0	24.0	Median	-4.0	-10.5	6.5
Std.Dev.	5.95	13.28	–	Std.Dev.	2.47	3.10	–

Note: The numbers in column Diff. measure the difference in leading months between CLI^W and CLI at turning points.

included, slightly modified with the inclusion of one additional expansionary phase as in Artis et al. (1995) and OECD (2002), with a trough 1980:7 and peak 1981:7. Table 3 lists the final reference chronology of US turning points for the comparison of the lead time at peaks and troughs of the two composite leading indicators.²⁰

In Table 3 we show for the two indicators, CLI and CLI^W , the number of leads in months with respect to peaks and troughs, along with the difference in leading months at each turning point between the two measures. The CLI^W gives signals of all turning points with a longer lead than CLI. For the CLI^W the average lead at peaks is 2.5 years, two years longer than the CLI, a leading time that is definitely too long to be useful in real time. This longer leading property with respect to peaks makes the CLI^W more useful as a signal of the end of the previous recessionary phase than as an indication of the approaching end of the current expansionary phase. This feature is clearly detectable from visual inspection of Figure 2.²¹

By contrast more interesting results emerge about the average lead time at troughs, with the CLI^W giving signals of turning points about six months in advance relative to the CLI. Moreover, since the value of the mean and median lead at troughs are equivalent, the signals provided by the CLI^W about approaching turning points can be considered as a reliable one.

4.2. CLI^W vs CLI derived measures

The leading behaviour of the CLI^W at turning points is not too dissimilar from that displayed by several measures derived from the (trend restored) CLI, such as the 6-month (annualised) and 12-month rate of change in the CLI. It is well known that these measures exhibit an extra lead time with respect to the CLI which is generally used to provide earlier and clearer signals for future turning points than the CLI itself, especially at downturns.²²

The leading time in months at troughs of CLI^W , CLI and its derived measures, that is, the 12-month and 6-month per cent changes in the CLI, are presented in Table 4. Two main

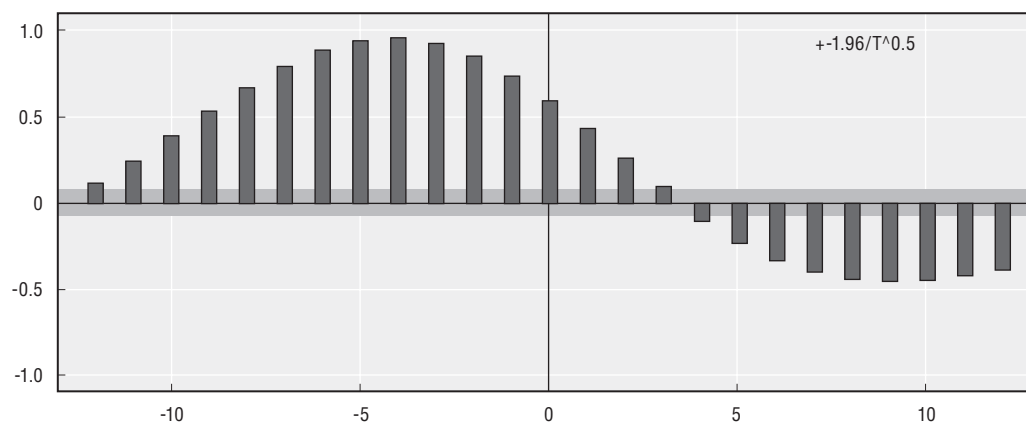
Table 4. **Leading time in months of CLI, 12-month CLI, 6-month CLI and CLI^W at troughs**

Troughs	CLI	CLI 12-month	CLI 6-month	CLI^W
1963:02	-5	-6 (-1)	-6 (-1)	-10 (-5)
1967:09	-7	-7 (0)	-10 (-3)	-15 (-8)
1970:11	-5	-7 (-2)	-9 (-4)	-13 (-8)
1975:04	-3	-4 (-1)	-5 (-2)	-9 (-6)
1980:07	-4	-4 (0)	-5 (-1)	-9 (-5)
1982:11	-6	-7 (-1)	-11 (-5)	-15 (-9)
1987:03	-4	-4 (0)	-7 (-3)	-8 (-4)
1991:09	-8	-8 (0)	-10 (-2)	-14 (-6)
1995:12	-1	-2 (-1)	-7 (-6)	-11 (-10)
2003:02	0	-3 (-3)	-5 (-5)	-6 (-6)
2005:05	-2	-2 (0)	-4 (-2)	-8 (-6)
Mean	-4	-4.91	-7.18	-10.83
Median	-4	-4	-7	-10.5

Note: In parenthesis the extra lead-time in months at troughs of different measures relative to the CLI.

results are in evidence: the first is the significant extra lead time, about three months, characterising the 6-month rate of change in the CLI relative to the CLI itself. This is a well known result that is common to other leading indicators such as the Conference Board LEI (Leading Economic Indicator), where the 6-month annualised rate of change of the LEI along with the so-called three Ds rule (duration, deepness and diffusion) is used to provide early warning signals of recession. The latter, and most important for our purposes, is the additional extra lead time that characterise the CLI^W relative to the 6-month per cent change in the CLI and that is greater than three months. Such extra leading time is also confirmed by the cross correlation function between the CLI^W with the 6-month per cent change in the CLI shown in Figure 4. Indeed, the general fit measured by the peak-correlation coefficient (0.93) is very good and indicates an average mean lead of about four months.

In sum, the wavelet-based composite indicator CLI^W seems to provide early warning signals of approaching lower turning points well in advance relative to the measures commonly derivable from the CLI, with the advantage that with this measure turning points have the same economic interpretation as the amplitude adjusted CLI.

Figure 4. **Cross-correlation between CLI^W at $t + i$ and 6-month (annualised) per cent change in the CLI at t .**

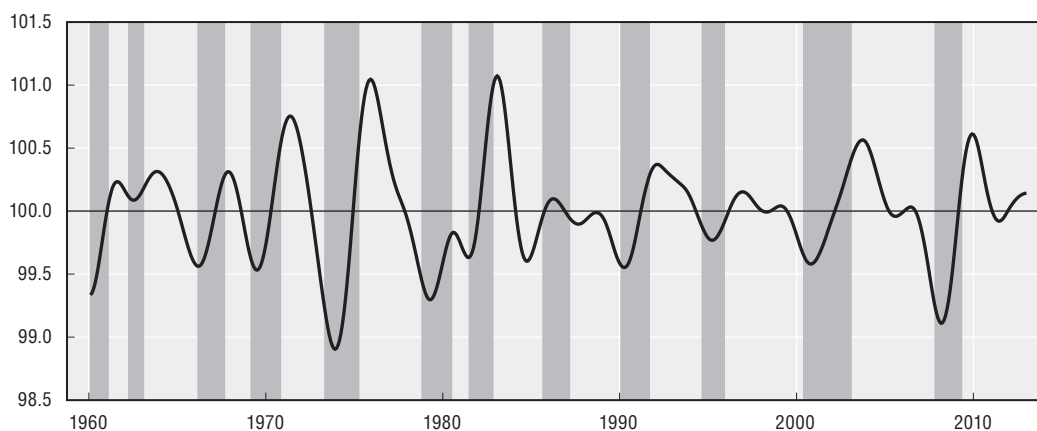
4.3. A smoothed version of the CLI^W

The reliability of signals provided by individual and composite indicators is assessed also in terms of the so-called false signals, that is the number of the extra or missing cycles relative to the reference chronology. Nonetheless their ability to provide early warnings signals of approaching turning points, the derived measures of the CLI need be taken with care since they are likely to provide false signals more frequently than the CLI, given that their cycles are shorter and more frequent. The same pattern seems to characterise the wavelet-based composite leading indicator CLI^W , as shown in Figure 1, where a number of extra cycles are in evidence in the comparison with the official OECD reference chronology. Since OECD chronology of turning points in the reference series takes into account only major cyclical swings, the extra cycles detected in the CLI^W are likely to be associated with several minor cycles. Indeed, most of these extra cycles coincide with turning points representing a number of minor cycles included in the previous OECD reference chronology (OECD, 2002).

According to Sargent (1979) major and minor business cycles can be distinguished on the basis of their periodicity. In particular, following NBER definitions if the cycle period is within the 2-4 years range the cycle is called a minor business cycle, otherwise the cycle is called a major business cycle. On the basis of Sargent's (1979) definition of 2-4 years for NBER minor cycles and frequency domain interpretation of each wavelet-based sub-index, it is possible to construct a wavelet-based composite indicator that distinguishes between major and minor cycles by removing fluctuations in the 16 to 32 months frequency range from CLI^W . Consequently, by excluding the CLI_{D_4} sub-index from the aggregate index CLI^W , we are able to obtain a composite leading indicator that, being characterised by fluctuations within the 32-128 frequency bands (that is between 3 and 10 years), can provide early signals to identify turning points representative of major cyclical swings only.

The wavelet-based index obtained by summing up the sub-indexes related to the D_6 and D_5 time scale components, $CLI_{6,5}^W$, is shown in Figure 5, with grey shaded areas representing the descending phase of the cycle (from peak to trough) according to OECD reference chronology. The comparison between the composite leading indicators in Figures 1 and 5 indicates that the $CLI_{6,5}^W$ has excellent leading properties, given its ability to provide early warnings of all the turning points and to largely reduce the risk of false

Figure 5. $CLI_{6,5}^W$ with OECD reference chronology for the US



signals.²³ Indeed, by removing the CLI_{D_4} sub-index from the aggregate composite index CLI^W corresponds to apply an extra smoothing procedure to CLI^W that tends to increase the degree of smoothness of $CLI_{6,5}^W$ and, via the attenuation of the influence of minor cycles, to provide fewer false signals.²⁴

5. Conclusions

This paper proposes a novel wavelet-based approach for constructing composite indexes that exploits the ability of wavelet analysis to select the individual components on a scale-by-scale, rather than aggregate, basis. The proposed methodology is applied to the OECD CLI for the US by constructing a composite leading indicator which combines several sub-indexes derived at scales corresponding to business cycle frequencies.

Our overall findings indicate that the selective use all available information in the frequency and time domain is likely to considerably improve the leading time in providing early signals of turning points in economic activity by retaining reliability of the signals provided, especially at troughs. Specifically, the comparison with the CLI and its derived measures indicate that the wavelet-based composite index has longer leading properties, since it gives early signals of recessions with a longer lead relative to CLI and its derived measures. Moreover, we show that by excluding from the wavelet-based index those components corresponding to the highest business cycle frequency band, that the frequency range between 16 and 32 months, and thus including the D_6 and D_5 components only, we can obtain a smoother version of the composite leading indicator with excellent leading properties as to the OECD reference chronology, and a reduced risk of false signals.

All in all, we believe that the ability of the wavelet-based approach to improve the quality and reliability of early signals of cyclical turning points relative to the actual system of composite leading indicators can be explained in terms of some practical considerations such as timeliness, smoothness and revision. Indeed, poor timeliness of component series, lack of overall smoothness of the CLI, and size of data revision are issues that can largely benefit from wavelet's ability to fully exploits the different informative content of individual indicators at different time scales.

Finally, a natural extension of this work involve a comparison of the proposed wavelet-based with the standard CLI using only the information set actually available at each point in the sample. Some very preliminary results of the real time properties of the proposed wavelet-based CLI as to OECD-CLI suggests that, although real time estimation of the wavelet components displays sensitivity to the availability of new data, the revisions tend to leave the early warning signalling content provided by the wavelet-based CLI unaltered, especially for its smoothed version.

Notes

1. Both the Conference Board and OECD have been using for years systems of composite indicators to yield qualitative information on current and future short-term movements in economic activity. More recently, after the US financial crisis of 2008-9, a large number of composite indicators have been also developed by government and international institutions with the aim to provide a measure of the degree of stress prevailing in the overall financial system (see Kliesen et al., 2012, for a recent survey of financial stress index for the US).
2. Extensions of the diffusion index have been proposed by Boivin and Ng (2005) and, more recently, by Heij et al. (2011), which propose a new method of leading index that explicitly takes into account the purpose of forecasting using principal covariate regression.

3. This notion replaces the view of NBER (Burns and Mitchell, 1946).
4. The parametric alternative is represented by the multivariate logit or probit regression approach.
5. Such component series, in order to be included in the composite index, are required to satisfy several economic criteria, such as economic rationale (reasoning) and wide coverage, as well as statistical criteria, like consistently timing behaviour (coincident, leading or lagging), statistical adequacy (in terms of quality and reliability of the data), importance of irregular and non-cyclical factors (smoothness) and timeliness (see Moore and Shiskin, 1967, for a comprehensive description of these criteria).
6. According to a time scale perspective aggregate data may be considered the result of a time scale aggregation procedure over all time scales, and thus the relationship between the aggregate variables are estimates averaged over all time scales.
7. The economic intuition supporting the application of time-frequency domain techniques in macroeconomics and finance is that many economic and financial processes are the results of decisions of agents with different, sometimes very different, time horizons information. For example, in financial markets the presence of heterogeneous agents with different trading horizons may generate very complex patterns in the time-series of economic and financial variables (for example, Muller et al., 1995; Lynch and Zumbach, 2003).
8. A brief introduction to wavelets in general, and the maximal overlap discrete transform in particular, is provided in Annex A.
9. Similar findings, using wavelet analysis, have been first obtained by Ramsey and Lampart (1998a, 1998b) for the consumption-income and the money-income relationships. More recently, Gallegati et al. (2013) have shown that interest rate spreads exhibit different informative content for future output at different time scales, while Gallegati and Ramsey (2013) have provided evidence about the different informative content of stock and bond market prices for investments at different time scales.
10. Previous examples of wavelet-based methods to construct composite indicators are provided in Picchetti (2008), and Rua and Nunes (2005). They differ from that proposed in the present contribution.
11. With longer leading properties we mean the ability to provide early signals of turning points in economic activity in advance relative to traditional composite indexes while retaining reliability of the provided signals.
12. By contrast the classical cycles approach is used, for example, by the Conference Board.
13. The similarities between wavelet and Fourier transform determines a correspondence between time scale components from wavelet decomposition and frequency bands from spectral decomposition (see Annex A). Specifically, the wavelet coefficients at different scale levels represent the signal in various frequency bands, with frequency being proportional to the inverse of the period. Since for all wavelets, there is a one-to-one relationship between scale and period, large time scales correspond to low frequencies, and short time scales to high frequencies.
14. The boundary method used in the wavelet decomposition is the reflection boundary condition. In this method an extension is made by pasting a reflected (time-reversed) version of the original signal of length T at its end and then applying a periodic boundary condition on the first T elements of the reconstructed signal (and omitting the remaining T elements).
15. Only in recent years has the OECD switched to a GDP-based business cycle target (see Fulop and Gyomai, 2012).
16. This statistical method can provide a reliable measure of the average lead of the indicator as well as the fit of the regression relationship under the assumptions of a linear relationship between variables and absence of extreme values. However, both problems are likely to be limited by performing cross-correlations calculations at time scale rather than aggregate level.
17. At each scale, the longer and shorter leading components are defined as those components whose average lead time is, respectively, above and below the median lead.
18. Indeed, this is the main objective of the OECD system of composite leading indicators.
19. These two statistical criteria, along with the number of missing or extra cycles, are generally used to evaluate the performance of the individual components of a composite indicator (and the composite indicator itself).
20. Growth cycle downswings (measured from peak to trough) in the modified OECD chronology are represented by grey shaded areas in Figures 1 and 2.

21. Indeed, when we analyse the cross-correlation results between the CLI^W and a reference series representing overall economic activity, such as the GDP ratio to trend, we find that the CLI^W is a countercyclical lagging indicator for the reference series.
22. Nonetheless, these derived measures have a different economic interpretation of peaks and troughs with respect to the “output-gap” interpretation of the amplitude adjusted CLI.
23. Although extra signals of turning points are now missing, there is evidence of a missing signal in the early 1960s for a turning point identified as a minor turning point by the former OECD chronology (OECD, 2002).
24. That quality of the CLIs may be improved either by replacing very irregular components with smoother ones or by introducing a more efficient smoothing technique is a well-recognised aspect in the OECD leading indicator methodology. Indeed, smoothness is probably the most important factor explaining revisions to the OECD CLI (Nilsson and Guidetti, 2007).

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ANNEX A

Wavelet analysis

Spectral analysis has been by far the most important filter processing tool in many fields (including economics) for many years and thus it may be helpful to provide a brief comparison between wavelet and Fourier based methods. Fourier and wavelet analysis have some strong similarities, but also important differences. Indeed, they both decompose a signal or a function into a sum of harmonic components and waves of different frequencies using different basis functions: sines and cosines in the Fourier transform, and wavelets in the wavelet transform. Specifically, the Fourier transform decomposes a signal or a function via a linear combination of Fourier basis functions (sines and cosines) that range over $\pm$ infinity, and the Fourier coefficients of the transformed function represent the contribution of each sine and cosine function at each frequency.

Although extremely useful as an alternative representation of the original time series, the Fourier transform has some serious drawbacks. First, the transformation to the frequency domain does not preserve the time information so that it is impossible to determine when a particular event took place. It tells us everything about the frequency structure of the signal, but nothing about the location of the events. In other words, it has only frequency resolution but not time resolution. Second, spectral decomposition methods perform a global analysis. Thus, in Fourier analysis a single disturbance affects all frequencies for the entire length of the series as all projections are globals, and thus the signal is assumed to be homogeneous over time. Thus, if the signal is a nonperiodic one, the summation of the periodic functions, sine and cosine, does not accurately represent the signal. Such a feature restricts the usefulness of the Fourier transform to the analysis of stationary processes, whereas most economic and financial time series display frequency behaviour that changes over time, that is, they are nonstationary (Ramsey and Zhang, 1995).

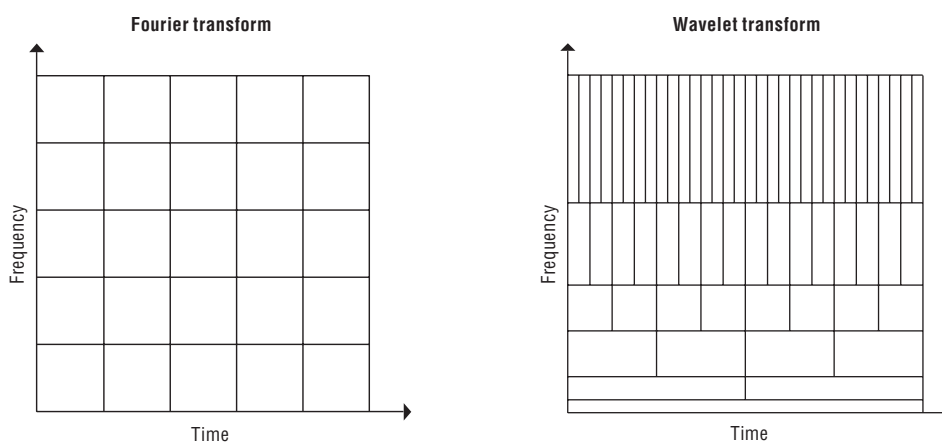
The windowed or short-time Fourier transform (WFT or STFT) can provide a partial solution to the problem of better representing a nonperiodic signal, because with the WFT the input signal is chopped up into sections, where each section is analysed for its frequency content separately. In particular, the windowed Fourier transform uses a fixed window function with respect to frequency and applies the Fourier transform to the windowed signal. The original signal is partitioned into small enough segments such that these portions of the non-stationary signal can be assumed to be stationary over the duration of the window function. The choice of the window length is based on the trade-off between the desired frequency resolution, which depends inversely on the duration of the window function, and the assumption of short-term stationarity. Once the window

function is determined, both the time as well as frequency resolutions become fixed for all frequencies and times, respectively. As a consequence, the short-term Fourier transform does not allow any change in resolutions in terms of time or frequency. The effect of the window is to localise the signal in time. The problem with this approach is the right choice of the window and, more importantly, its constancy over time.

Thus, the Fourier transform is a frequency domain representation of a signal containing the same information as the original function, but summarised as a function of frequency. The Fourier transform contains as basis functions sines and cosines, while the wavelet transform contains more complex basis functions called wavelets. But while the Fourier transform has a single set of basis functions, that is, the sine and cosine functions, wavelets have transforms based on an infinite set of possible basis functions and thus may provide immediate access to information that can be obscured by Fourier analysis.

Wavelet analysis may overcome the main problems evidenced by Fourier analysis and the short-time Fourier transform.¹ The wavelet transform uses a basis function that is dilated or compressed (through a scale or dilation factor) and shifted (through a translation or location parameter) along the signal so as to provide a time-frequency representation where all the information is associated with specific time horizons and locations in time. Hence, a wavelet is similar to a sine and cosine function in that it also oscillates around zero, but differ because, as wavelets are constructed over finite intervals of time, they are well-localised both in the time and the frequency domain. In contrast to Fourier analysis, wavelets are compactly supported as are all projections of a signal onto the wavelet space which are essentially local, not global and thus need not be homogeneous over time. Indeed, much of the usefulness of wavelet analysis has to do with its flexibility in handling a variety of nonstationary signals. Wavelets, in opposition to time and frequency domain analyses, consider nonstationarity an intrinsic property of the data rather than a problem to be solved by pre-processing the data. In particular, since the base scale includes any non-stationary components, the data need neither be detrended nor differenced (Schleicher, 2002).

Figure A1. **The windowed Fourier transform and the wavelet transform partitioning of the time-frequency plane.**



An immediate way to see the time-frequency resolution differences between the windowed Fourier transform and the wavelet transform is to look at the basis function coverage of the time-frequency plane. Figure A1 shows the time-frequency resolution properties of the windowed Fourier transform (upper panel) and the wavelet transform (lower panel). It shows that, unlike the windowed Fourier transform which has constant resolution at all times and frequencies, the wavelet transform, through the adaptive partition of the time-frequency plane, analyses the signal at different frequencies with different resolutions using a multiresolution analysis. Thus, in contrast to the fixed time-frequency partition of the windowed Fourier transform the wavelet transform provides good frequency resolution (and poor time resolution) at low frequencies and good time resolution (and poor frequency resolution) at high frequencies.² In summary, the multiresolution analysis approach may overcome the resolution problem as it adaptively partitions the time-frequency plane, using short windows at high frequencies and long windows at low frequencies, and thus letting both time and frequency resolutions to vary in time frequency plane.

We now recall the basic structure of the wavelet approach. Wavelets, their generation, and their potential use are discussed in intuitive terms in Ramsey (2008). Gencay et al. (2002) and Crowley (2007) generate an excellent development of wavelet analysis and provide many interesting economic examples. Percival and Walden (2000) provides a more technical exposition with many examples of the use of wavelets in a variety of fields, but not in economics. At the simplest level wavelet analysis consists of a transformation of a signal obtained by projecting the signal onto a sequence of local basis functions, each expressible as

$$g(t) = \frac{1}{\sqrt{s}} g\left(\frac{t-k}{s}\right) \quad (5)$$

where the time scale s corresponds to the width of the wavelet function $g(t)$, and k is the wavelet shift along the time axis.

There are two basic wavelet functions: the father-wavelet, ϕ , and the mother-wavelet, ψ . The formal definition of the father wavelets is the function

$$\phi_{j,k} = 2^{-\frac{j}{2}} \phi\left(\frac{t-2^j k}{2^j}\right) \quad (6)$$

defined as non-zero over a finite time length support that corresponds to given mother wavelets

$$\psi_{j,k} = 2^{-\frac{j}{2}} \psi\left(\frac{t-2^j k}{2^j}\right) \quad (7)$$

with $j = 1, \dots, J$ in a J -level wavelets decomposition. The former integrates to 1 and reconstructs the longest time-scale component of the series (trend), while the latter integrates to 0 (similarly to sine and cosine) and is used to describe all deviations from trend.³

The application of the basic wavelet functions to the signal allows one to compute the wavelet series coefficients at all scales given by

$$\begin{aligned} w_{j,k} &= \sum_k \psi_{j,k} f(t) \\ v_{j,k} &= \sum_k \phi_{j,k} f(t) \end{aligned}$$

where the coefficients w_{jk} and v_{jk} are the projections of the time series onto the mother and father wavelet functions, respectively. The two types of coefficients are sometimes referred to as wavelet and scaling coefficients, respectively. Wavelet coefficients at level j are related to changes of averages over a range of different scales (usually taken to be powers of two), and, in particular, are proportional to differences between local averages of the data taken at that scale. On the other hand, the scaling coefficients at level j are proportional to the local average of the data at that scale and therefore can be associated with averages on a specified scale.⁴

A wavelet transform decomposes a given function into coefficients from which the original function can be reconstructed using an inverse wavelet transformation. The wavelet representation of the signal or function $f(t)$ in $L^2(\mathbb{R})$ is represented by

$$f(t) \approx \sum_k v_{J,k} \phi_{J,k}(t) + \sum_k w_{J,k} \psi_{J,k}(t) + \dots + \sum_k w_{j,k} \psi_{j,k}(t) + \dots + \sum_k w_{1,k} \psi_{1,k}(t) \quad (8)$$

where J is the number of multiresolution components or scales, and k ranges from 1 to the number of coefficients in the specified components. The multi-resolution decomposition of the original signal $f(t)$ is given by the following expression

$$f(t) \approx V_J + W_J + W_{J-1} + \dots + W_j + \dots + W_1 \quad (9)$$

where $V_J = \sum_k v_{J,k} \phi_{J,k}(t)$ and $W_j = \sum_k w_{j,k} \psi_{j,k}(t)$ with $j = 1, \dots, J$. The sequence of terms $V_J, W_J, \dots, W_j, \dots, W_1$ in (4) represents a set of signal components that provide representations of the signal at different resolution levels 1 to J , with the detail signals W_j providing the increments at each individual scale or resolution level. Thus, wavelet analysis enables us to separate the increments at each individual scale, or resolution, level, we are able to examine the relationship between the variables when the variation in each variable has been restricted to a specific indicated scale.

Notes

1. For example, the set of frequencies used in Fourier analysis are themselves dilations of the fundamental frequency. See Gabor (1946).
2. Because a single window is used for all frequencies in the WFT, the resolution of the analysis is the same at all locations in the time-frequency plane.
3. The mother wavelets, as said above, play a role similar to sines and cosines in the Fourier decomposition. They are compressed or dilated, in time domain, to generate cycles fitting actual data.
4. Mother wavelet acts as a high-pass filter and delivers the detailed information of the function, while father wavelet serves as a low-pass filter and represents the coarsest information of the function. Thus, we may say that the low-pass filter averages, while the high-pass filter differences.

Turning point chronology for the euro area: A distance plot approach

by

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We propose a transparent way of establishing a turning point chronology for the euro area business cycle. Our analysis is achieved by exploiting the concept of recurrence plots, in particular distance plots, to characterise and detect turning points of the business cycle. Firstly, we apply the concept of recurrence plots on the US Industrial Production Index (IPI) series; this serves as a benchmark for our analysis since it already contains a reference chronology for the US business cycle, as provided by the Dating Committee of the National Bureau of Economic Research (NBER). We then use this concept to construct a turning point chronology for the euro area business cycle. In particular, we show that this approach detects turning points and helps with the study of the business cycle without a priori assumptions on the statistical properties of the underlying economic indicator.

Keywords: economic cycles; euro area; recurrence plots; turning points

JEL classification: C14, C40, E32

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1. Introduction

Since the early work by Burns and Mitchell (1946), many attempts have been made to measure and forecast business cycles. The main aim of business cycle analysis is to detect and anticipate economic fluctuations with a particular attention paid to turning points location (Anas et al., 2008). There are a great number of articles on national chronology dating (for example, Belgium, UK, Canada, Austria and Australia); however, very few countries have official dating procedures (among them the USA National Bureau of Economic Research [NBER], and Japan Economic and Social Research Institute). Since the establishment of the euro area, several papers have been devoted to its cyclical dating. However, an official dating does not yet exist for the euro area. Dating is an *ex post* exercise, and in this respect, accuracy is an important criterion since dating is useful for economic decision-making. Governments and central banks are usually very sensitive to indicators showing signs of deterioration in growth as it allows them to adjust their policies sufficiently in advance, avoiding more deterioration or a recession. In this respect, timing is important and the earlier the signal, the better (Anas et al., 2007). It is worth noting that the announcement of the cycle of turning point dates in the United States (US) is often substantially delayed.¹ As such, it will be interesting to propose methods that will enhance faster and more accurate detection of these dates.

In literature, two types of cycles are usually considered: the classical business cycle and the growth cycle. The classical business cycle refers to fluctuations in the level of the underlying economic indicator while the growth cycle refers to the deviations from the long-term trend of the series. The growth cycle has not been studied much compared to the classical business cycle due to the de-trending problem of this concept (Artis et al., 2003a; Anas et al., 2007). In this paper, we study the classical business cycle using monthly data to enhance accuracy of the dating. The most commonly dated monthly time series is the industrial production (Artis et al., 2002, 2003a, 2003b; Anas et al., 2007). Our aim is to propose a method with these features:

1. Robustness to extreme values, non stationarity and to any length of data.
2. It must be replicable by anyone. This enhances the transparency of the method.
3. Adaptability of the method to different time series.
4. The chronology would not be revised through time.

Recurrence Plot (RP) is an advanced graphical technique of nonlinear data analysis, which reveals all the times when the phase space trajectory of a dynamical system visits roughly the same area in the phase space. The phase space trajectory of a system refers to the path traced in a high-dimensional space representing the time evolution and the dynamics of the system. Although most applications of this technique have been in physics and biology, it has gained interest in a variety of scientific fields (Marwan et al., 2007; Marwan, 2008).² Recurrence plots and recurrence quantification analysis (Zbilut and Webber, 1992; Marwan et al., 2002) is also gaining some attention in economics (see, for

example, Kyrtsov and Vorlow, 2005; Strozzi et al., 2008; Belaire-Franch, 2004; Holyst et al., 2001; Addo et al., 2013). This technique is applicable to any time series since it requires no *a priori* assumptions on the statistical properties, such as stationarity or mathematical structure of the time series. We find this technique as a promising means of analysing economic data since it is robust against non-stationarity (Marwan et al., 2007). In this work, we mainly use distance plots (sometimes called “unthresholded recurrence plots”) in studying the turning points of business cycles. Whilst the central focus of this paper is the analysis of univariate time series (Industrial Production Index), we also provide the reader with possible extensions beyond the scope of the paper in order to clarify the methodology.

Previous works documenting the euro area business cycle are quite limited by: stationarity of data, choice of filters and usually model-based approaches (see Hamilton, 1989; Harvey and Trimbur, 2003; Artis et al., 2002, 2003b; Hodrick and Prescott, 1997; Anas et al., 2007; Anas and Ferrara, 2006; Bengoechea and Perez-Quiros, 2004; McAdam, 2003; Monch and Uhlig, 2005; Harding, 2004; Fagan et al., 2001). For instance, the work by Monch and Uhlig (2005) first constructs a euro area monthly real GDP series by interpolation and then applies a modified version of a nonparametric algorithm, the Bry-Boschan procedure (Bry and Boschan, 1971), to determine peaks and troughs in univariate time series. It is unclear whether information is lost or gained after such interpolation. It is worth noting that the proposed Bry-Boschan procedure by Monch and Uhlig (2005) as a turning point selection method is unsuitable when multivariate time series are considered for dating. To our best of knowledge, most of the existing dating methodologies are restrictive in terms of assumptions on model specification and usually unsuitable for short and non-stationary data. As such, we propose an alternative methodology using the concept of recurrence plots, which is essentially a data-driven approach with no *a priori* assumptions on the statistical properties on the underlying economic indicator(s). This concept of recurrence plots can be applicable to both univariate and multivariate time series (Marwan and Kurths, 2002; Romano et al., 2005).

Our aim is to construct a turning point chronology for the euro area business cycle. Our analysis exploits the concept of recurrence plots on an underlying economic indicator to locate hidden patterns, non-stationarity and to examine the nature of these plots in events of economic crisis. The qualitative interpretation of our results relates the existence of disruptions (butterflylike or band structures) to the non-stationarity, rare states (extreme events) or far from the normal, transitions (Eckmann et al., 1987; Marwan et al., 2007; Marwan, 2008; Addo et al., 2013).

The paper is organised as follows: We provide in Section 2, an overview on the concept of recurrence plots and distance plots. In Section 3, we present a comprehensive analysis of the feasibility of this approach to analyse both the US and euro area economic cycle. Section 4 concludes.

2. Methodology based on recurrence plots

The method of recurrence plots (RP) was introduced to visualise the dynamics of phase space³ trajectories (Eckmann et al., 1987; Marwan, 2008). It is a graphical technique that depicts the different occasions when a dynamical system visits roughly the same area in the phase space. From Takens’ embedding theorem (Takens, 1981), the dynamics can be appropriately presented by a reconstruction of the phase space trajectory⁴ $\vec{x}(t) = \vec{x}_i \in \mathbb{R}^m$ ($i = 1, \dots, n, t = i\Delta t$, where Δt is the sampling rate) in the m -dimensional phase space.

For a given one-dimensional time series $\{u_i\}_{i=1}^N$, the phase space vectors $\bar{x}$ can be reconstructed by embedding the series using Takens' time delay method $\bar{x}_i = (u_i, u_{i+\tau}, \dots, u_{i+(m-1)\tau})$. The co-ordinates of this vector correspond to the present and lead values of the time series. The parameters m and τ are referred to as the embedding dimension and time delay respectively (Takens, 1981; Marwan et al. 2007; Addo et al., 2012b). The choice of m and τ are usually based on methods for approximating these parameters, such as the false nearest neighbours method (for m) and mutual information (for τ), which ensures the entire covering of all free parameters and avoiding auto-correlated effects (Kantz and Schreiber, 1997). Gautama et al. (2003) proposed a differential entropy-based method in which a single measure is simultaneously used to obtain the embedding dimension, m , and time lag, τ . We refer the interested reader to Gautama et al. (2003) and Addo et al. (2012a, 2013) for an overview of this method. We refer to the case for which $m = 1$ and $\tau = 1$ as an unembedded time series. The recurrence plot is the calculation of an $\eta \times \eta$ matrix

$$R_{i,j}^x = \begin{cases} 1 & : \|\bar{x}_i - \bar{x}_j\| < \varepsilon \\ 0 & : \text{otherwise} \end{cases} \quad \bar{x}_i \in \mathbb{R}^m, i, j = 1, \dots, \eta, \quad \eta = N - (m-1)\tau, \quad (1)$$

where $\|\bullet\|$ is a norm (for example, Euclidean or maximum norm) and ε is the cut-off distance which defines a region centred at $\bar{x}_i$. If $\bar{x}_j$ falls within this region, the state will be near to $\bar{x}_i$ and is taken to be a recurrence of the state $\bar{x}_i$, which implies $R_{i,j}^x = 1$. The recurrence plot is square matrix plot of the binary values $R_{i,j}^x$, in which the matrix element correspond to those calendar times at which a state of a dynamical system recurs (columns and rows correspond then to a certain pair of calendar times) (Marwan et al., 2007; Addo et al., 2013 and the references therein). In general, the cut-off distance ε has to be chosen as small as possible, however a too small ε can lead one to miss some structure if there is noise distortion (Marwan, 2008). Zbilut and Webber (1994) suggest setting a threshold level equal to the lower 10% of the maximum distance between the embedded vectors. In literature, further variations of the recurrence plots have been proposed for different purposes.⁵ In this paper, we make use of a special type of recurrence plot referred to as unthresholded recurrence plots (Iwanski and Bradley, 1998). This recurrence plot is obtained by plotting a matrix of distances

$$D_{i,j}^x = \|\bar{x}_i - \bar{x}_j\| \quad (2)$$

between the vectors $\bar{x}_i$ and $\bar{x}_j$. The matrix data obtained from the application of Equation 2 is graphically represented as colours making it easier to read. In other words, the unthresholded recurrence plot is a heat map (colour map) of the distance matrix obtained from Equation 2. As such, it is appropriate to term the unthresholded recurrence plot as distance plot. In the section that follows, we will often use the term "distance plot" and "unthresholded recurrence plot" interchangeably. Multivariate extensions of recurrence plots have been developed as cross recurrence plots and joint recurrence plots (Marwan and Kurths, 2002; Romano et al., 2005). In comparing the dynamics of any two time series simultaneously embedded in the same phase space, we employed the cross recurrence plot (Zbilut et al., 1998; Marwan and Kurths, 2002; Addo et al., 2013). This is useful in studying the simultaneous occurrence of a state in both series. The cross

recurrence plot entails testing for closeness of each point of the first trajectory $\bar{x}_i (i=1, \dots, \eta)$ with each point of the second trajectory $\bar{y}_j (j=1, \dots, \vartheta)$ resulting in $\eta \times \vartheta$ array

$$CR_{i,j}^{xy} = \begin{cases} 1 : \|\bar{x}_i - \bar{y}_j\| < \varepsilon \\ 0 : otherwise \end{cases} \quad (3)$$

Thus, the purpose of cross recurrence plot (CRP) is to compare the states of two systems, which means that the states represent the same physical system, that is, the data should have the same unit and the phase space reconstruction must be the same. We employ the CRP in comparing US IPI and euro area IPI since both time series have the same unit⁶ and phase space reconstruction (Marwan et al., 2007, 2002; Marwan and Kurths, 2002; Addo et al., 2013).

In contrast to cross recurrence plots, joint recurrence plot (JRP) shows all those times at which a recurrence in one dynamical system occurs simultaneously with a recurrence in a second dynamical system. In other words, the JRP is the element-wise product of the recurrence plot of the first system and the recurrence plot of the second system, that is, for two systems $\bar{x}$ and $\bar{y}$, the joint recurrence plot is

$$JR_{i,j}^{xy} = R_{i,j}^x \cdot R_{i,j}^y, \bar{x}_i \in \mathbb{R}^m, \bar{y}_j \in \mathbb{R}^n, i, j = 1, 2, \dots, \eta\vartheta \quad (4)$$

JRPs can be computed from more than two systems. The dimension of the considered systems in phase spaces can be different but the data length has to be the same. Joint recurrence plots can be used in order to detect phase synchronisation (Marwan et al., 2007; Marwan and Kurths, 2002; Romano et al., 2005). For example, in the US, the NBER uses several indicators (such as gross domestic product, personal income, household employment, Industrial production Index, gross domestic income, payroll employment, manufacturing and retail sales) to date recessions. Considering this multivariate time series, in which the seven univariate time series are usually not of the same unit, the joint recurrence plot is more suitable to compare their recurrences, that is, whether the recurrences of states in processes separately occur at the same times. We remark that the concept of JRP is beyond the scope of the paper and it is only provided in order to clarify the methodology.

Recurrence plots contain typical small-scale⁷ structures, and in particular, large-scale structure called texture, as caused by the characteristic behaviour of the phase space trajectory of systems. These large-scale structures can be visually characterised by homogeneous, periodic drift or disrupted (Eckmann et al., 1987; Marwan et al., 2007; Marwan, 2008; Zbilut and Webber, 1992). The visual appearance of these plots gives hints about the dynamics of the system. The qualitative interpretation of the existence of disruptions (butterfly-like or band structures) are the result of non-stationarity, some states are rare or far from the normal, or, where transitions may have occurred (Eckmann et al., 1987; Marwan et al., 2007; Marwan, 2008). We refer to the existence of such butterfly-like structures along the main diagonal of the recurrence plot as an indication of economic crisis, where the turning points are identified as the start and end of the formation of these structures. It is worth noting that we mainly use the distance plots in identifying the turning points in each univariate time series (principally IPI of the US and euro area) and then the cross recurrence plots in studying the simultaneously recurrence of states in both series. The distance plot is replicable by definition since it is obtained by plotting a matrix of distances $D_{i,j}^x$, in Equation 2, which do not change through time for a given time series.

This ensures an effective dating chronology since it avoids revision through time for an underlying economic indicator. The main advantage of recurrence plots is that they provide useful information even for short and non-stationary data, where other methods fail (Marwan et al., 2007). The following section will be devoted to dating the euro area business cycle.

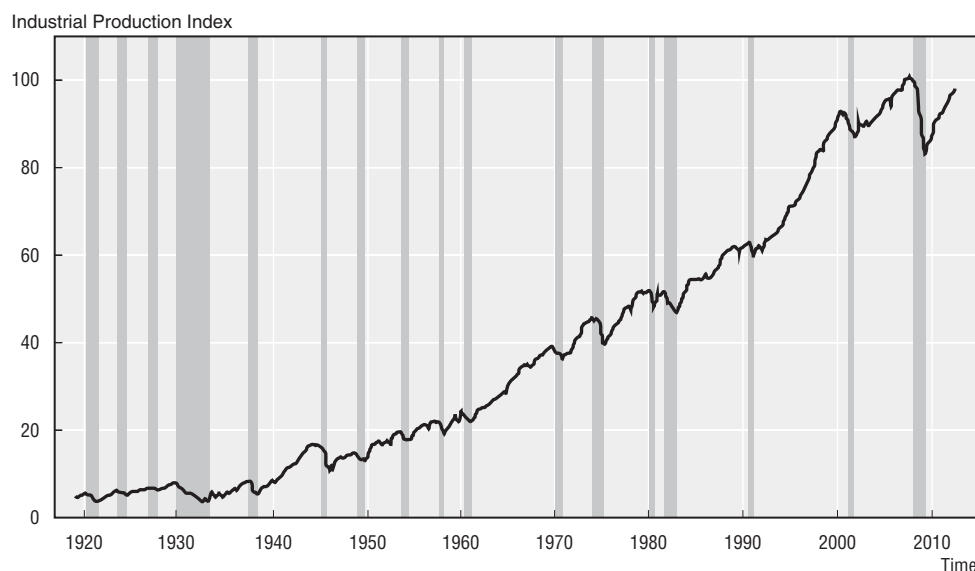
3. Data analysis

In this section, we perform analysis to characterise and detect turning points for the euro area economic cycle considering the monthly Industrial Production Index (IPI) series. Firstly, we exploit the concept of recurrence plots⁸ on the US IPI series to characterise and detect recessions periods. The essence of starting the analysis with the US data is to serve as a benchmark for our analysis since the reference chronology for the US business cycle already exists, as provided by the Dating Committee of the National Bureau of Economic Research (NBER). We then use this concept in constructing a monthly turning point chronology for the euro area business cycle. In particular, we show that this approach permits to detect turning points and study the business cycle without *a priori* assumptions on the statistical properties on the underlying economic indicator.

The monthly US Industrial Production Index (IPI) time series⁹ spanning over the period January 1919 to July 2012 is considered for the data analysis. Figure 1 is the plot of the monthly IPI series for the period: 1919:01 2012:07, implying 1123 observations, where the shaded regions corresponds to NBER published dates for US recessions from 1920.¹⁰ Figure 2 is the plot of monthly euro area IPI series for the period: 1971:01 2011:12 ($n = 492$).

Figure 1. **US Industrial Production Index (IPI)**

Monthly, 1919:01 2012:07, ($n = 1123$)

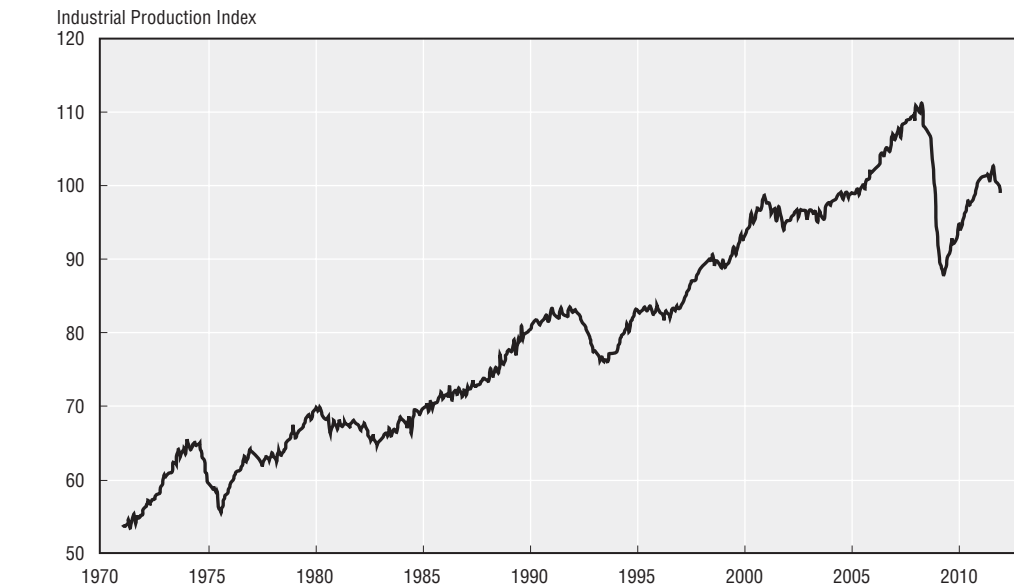


Note: The shaded regions correspond to the US recessions from 1920 as published by NBER.

Figure 3 shows the unthresholded recurrence plot, sometimes termed “distance plot” (Iwanski and Bradley, 1998), on the US IPI. It is a matrix plot with both vertical and horizontal axes that correspond to calendar dates. The colour map corresponds to the distance to the next recurrence of a state in the time series. In this paper, we mainly consider the case when the embedding parameters are $m = 1$ and $\tau = 1$ since the results

Figure 2. **Euro area Industrial Production Index (IPI)**

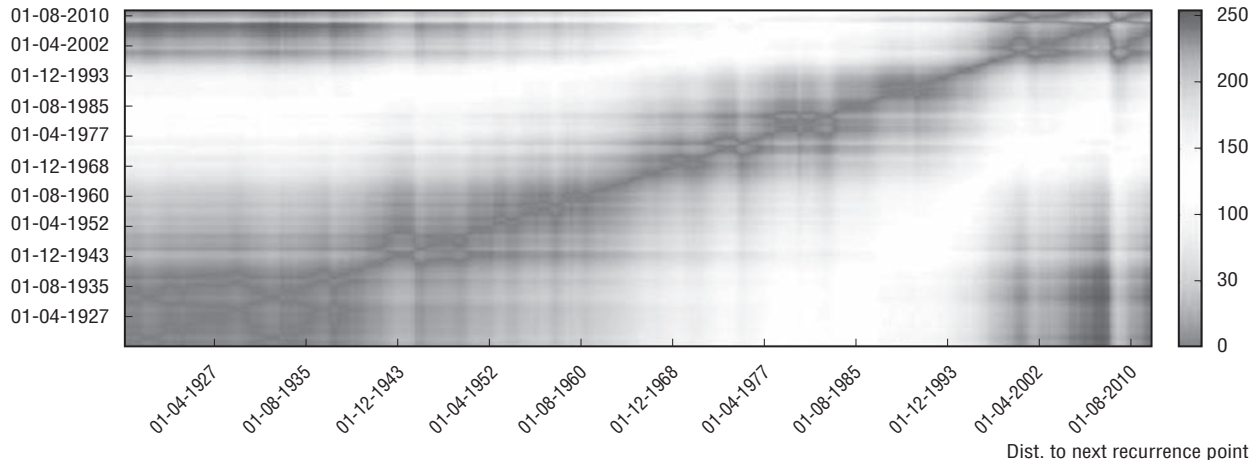
Monthly, 1971:01–2011:12, (n = 492)



Source: Billio and Casarin (2010) and Eurostat.

Figure 3. **Unthresholded recurrence plot of the US IPI**

Distance Matrix Dimension: 1, Delay: 1



Note: This is an unthresholded recurrence plot which is sometimes termed “distance plot” (Iwanski and Bradley, 1998). It is a matrix plot with calendar time on both the vertical and horizontal axes. The colour map corresponds to the distance to the next recurrence of a state in the time series. This representation shows the distances between states and enhance understanding of the phase space trajectory of US IPI. The existence of butterfly-like structures, of a minimum size of six months, along the main diagonal (bisector) indicates economic crisis. In this case, the start and end of a economic crisis corresponds the start and end on the formation of butterfly-like structure along the main diagonal.

obtained for unembedded and embedded version of the time series do not differ in terms of identification of the turning points associated with the business cycle (Addo et al., 2013). The recurrence plot provides a graphical understanding of the dynamics of phase space trajectories, of the time series, as distances between states are revealed. The recurrence plots allow users to study the recurrence of a state at a particular calendar date. In other words, fixing a period or date on the horizontal axis, we are able to observe the recurrence of such events along the calendar dates on the vertical axis. Intuitively, the plot depicts the different

occasions when the economic system, described by IPI, visits roughly the same area in the phase space. The existence of butterfly-like structures along the main diagonal (bisector) of the plot indicates economic crisis as discussed in Section 2. In this case, the start and end of a declining economic activity corresponds the start and end of the formation of butterfly-like structure along the main diagonal. In this paper, we designate any butterfly-like structure with a minimum size of six months as economic crisis.¹¹ Our results on the dating chronology obtained from the distance plot for US IPI (Figure 3) are presented in Table 1.

Table 1. **Business cycle peaks and troughs in the United States, 1920-2009**

NBER dates		Butterfly dates	
Peak	Trough	Peak	Trough
1920:01	1921:07	1920:02	1921:08
1923:05	1924:07	1923:05	1924:08
1926:10	1927:11	1926:10	1927:11
1929:08	1933:03	1929:08	1933:04
1937:05	1938:06	1937:05	1938:02
1945:02	1945:10	1945:02	1945:10
1948:11	1949:10	1948:08	1949:10
1953:07	1954:05	1953:07	1954:01
1957:08	1958:04	1957:09	1958:04
1960:04	1961:02	1960:01	1961:03
1969:12	1970:11	1969:10	1970:11
1973:11	1975:04	1974:09	1975:04
1980:01	1980:07	1980:00	1980:08
1981:07	1982:11	1981:08	1983:01
1990:07	1991:03	1990:08	1991:03
2001:03	2001:11	2000:09	2001:11
2007:12	2009:06	2007:12	2009:06

Notes: The peak and trough dates, in the format YYYY:MM, represent the start and end of “episodes” of some sort. The column NBER are the reference chronology for US business cycles published at www.nber.org/cycles.html. The results of turning points obtained from the distance plot of US IPI is displayed in column labelled butterfly dates.

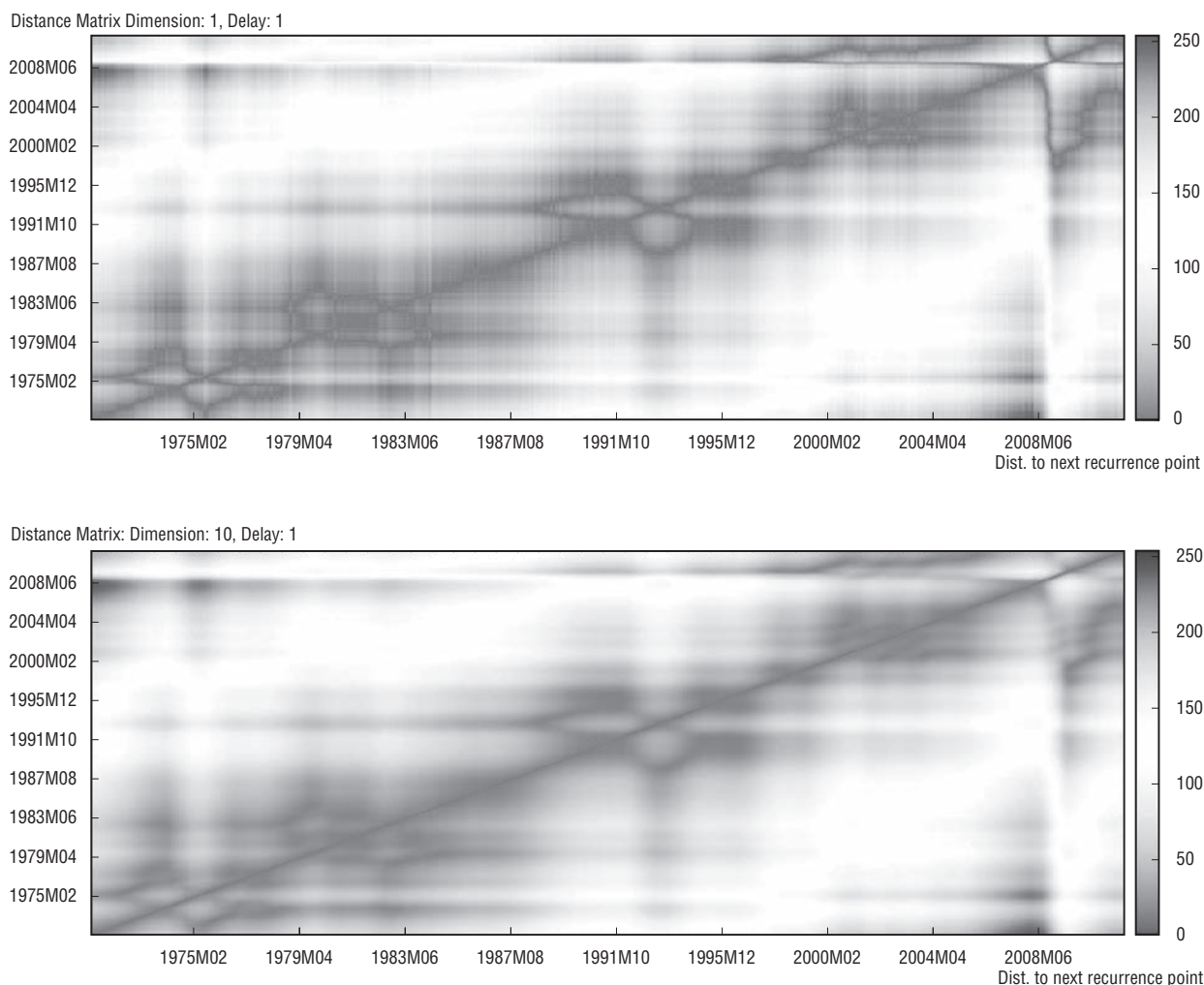
Sensitivity analysis on the distance plot with respect to the embedding dimension m and the time delay τ reveals that for fixed $\tau = 1$ and for any chosen $m > 1$, the turning points identified are same as setting $m = 1$ and $\tau = 1$. In particular, we observe much sharper picture of the butterfly-like structures as the embedding dimension is set close to 1. We noticed that for any given m , as the time delay parameter increases ($\tau \geq 1$), the butterfly-like structures grow dimmer making it not easy to clearly identify the peaks and troughs of the business cycle. As such, we recommend that the time delay parameter be set to 1 for better identification of turning points.

The dates from the distance plot for US IPI (Figure 3) appear not to differ much from the official business cycle dates published by NBER. Interestingly, the main difference occurs in the detection of the peak date of two recession periods: 1973 and 2001 (see Table 1). Our findings also indicate that the turning points provided by NBER for the US can be obtained with only IPI data using the distance plot approach. Thus, this results on the preliminary exploratory analysis for the US provides support for the use of our propose procedure to dating the euro area business cycle.

In the following, we focus on detecting and constructing the turning points for the euro area business cycle. We proceed with the same analysis as done with the US data but

now using the euro area IPI series. We remark that embedding the original time series does not yield different results in terms of identification of the turning points associated with the business cycle. Our results on the dating chronology of the euro area based on the IPI are presented in Table 2 with the distance plot in Figure 4. A comparison of turning points for the euro area considering dates identified by the distance plot and in Anas et al. (2007) for the monthly series of euro area IPI, is given in Table 3. The quarterly turning points provided by the Centre for Economic Policy Research (CEPR) using the euro area real GDP and the Monch and Uhlig (2005) turning points identified by the Bry-Boschan algorithm when applied to the Moench/Uhlig (MU) monthly series of euro area real GDP are also provided in Table 3. Notice that the dates determined by the distance plot procedure do not differ much from the turning points already provided by CEPR and two other dating chronologies. In particular, our proposed dates come close to the monthly turning points proposed in Monch and Uhlig (2005) by within a few months.

Figure 4. **Distance plot for the euro area IPI and its embedded version**



Note: The existence of butterfly-like structures, of a minimum size of six months, along the main diagonal (bisector) indicates economic crisis. Embedding the original time series does not yield different results in terms of identification of the turning points associated with the business cycle.

Table 2. **Industrial business cycle dating chronology for the euro area from 1971-2011**

Butterfly dates	
Peak	Trough
1974:06	1975:08
1980:01	1980:10
1982:05	1982:12
1992:04	1993:06
2000:12	2001:11
2007:12	2009:04
2011:07	—*

Notes: The peak and trough dates, in the format YYYY.MM, represent the start and end of “episodes” of some sort.

* The end of the last recession period that started 2011:07(q3) was not determined considering the sample period.

In Figure 5, we provide the distance plots for the US IPI and euro area IPI for the period 1991:01 to 2012:07. The simultaneous occurrence of economic crisis in both the US and euro area for this period can be visualised on the cross recurrence plot displayed in Figure 6. These two economic systems were both hit by the crisis resulting from the dot-com bubble burst, and even more during the 2007-12 global financial crisis. Similar features in the plots for this period suggests strong economic interdependence between the US and euro area economic systems.

Table 3. **Comparison of turning points for the euro area**

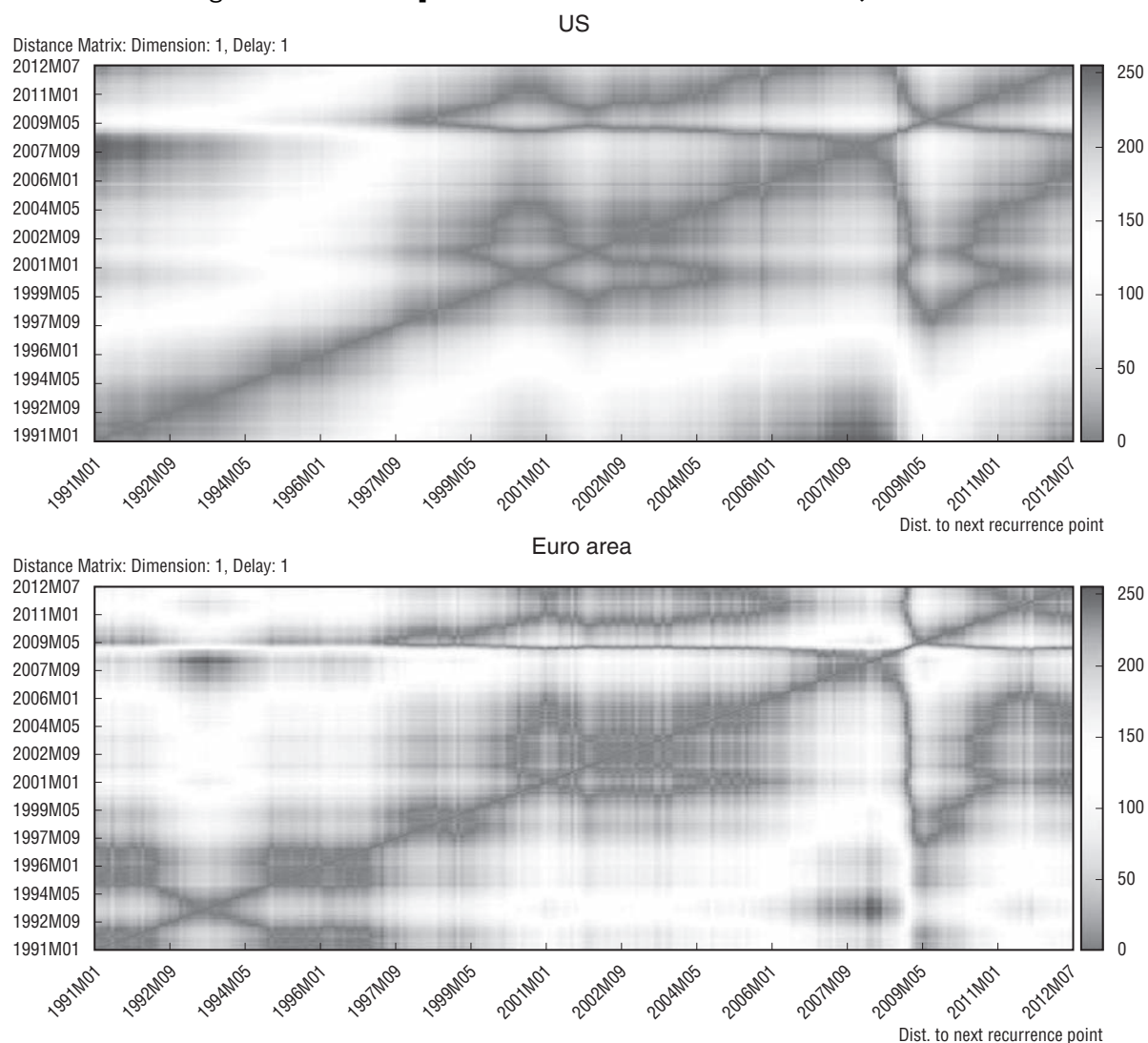
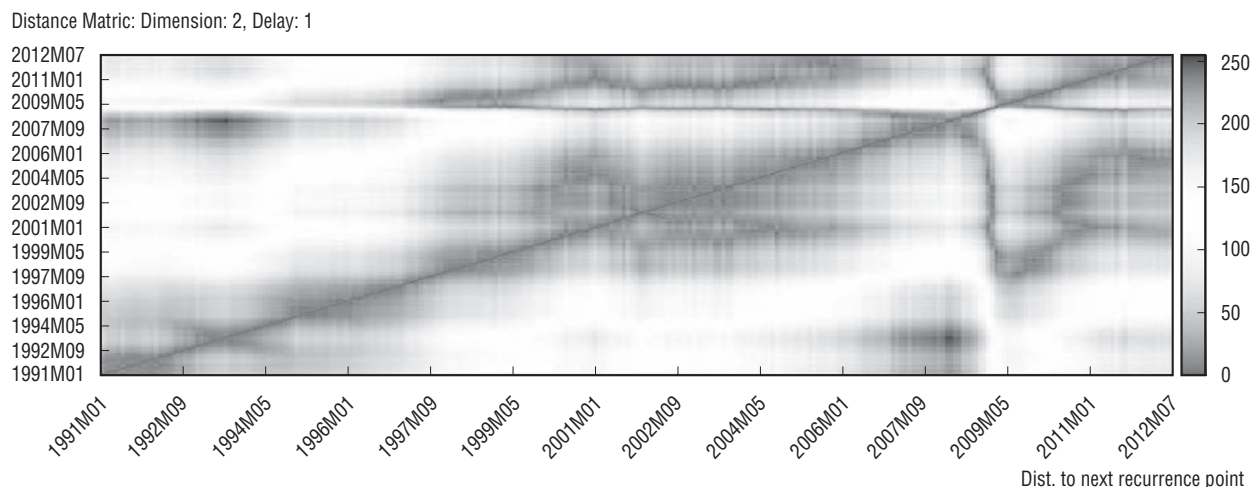
Butterfly dates		Anas et al. (2007) dates		CEPR dates		MU dates	
Peak	Trough	Peak	Trough	Peak	Trough	Peak	Trough
1974:06(q2)	1975:08(q3)	1974:04(q2)	1975:04(q2)	1974:xx(q3)	1975:xx(q1)	1974:08(q3)	1975:04(q2)
1980:01(q1)	1980:10(q4)	1980:02(q1)	1981:01(q1)	1980:xx(q1)	1982:xx(q3)	1980:03(q1)	1980:09(q3)
1982:05(q2)	1982:12(q4)	1981:10(q4)	1982:12(q4)	—	—	1982:04(q2)	1982:07(q3)
1992:04(q2)	1993:06(q2)	1992:01(q1)	1993:05(q2)	1992:xx(q1)	1993:xx(q3)	1992:02(q1)	1993:01(q1)
2000:12(q4)	2001:11(q4)	2000:12(q4)	2001:12(q4)	—	—	—	—
2007:12(q4)	2009:04(q2)	—	—	2008:xx(q1)	2009:xx(q2)	—	—
2011:07	—*						

Notes: The format of the dates “yyyy:mm(qq)” denotes “year:month(quarter)”. The butterfly dates corresponds to peaks and troughs identified by the distance plot when applied to the monthly series of euro area IPI. The turning points obtained in Anas et al. (2007) for the monthly euro area IPI series is denoted as Anas et al. (2007) dates. The CEPR dates are the quarterly turning points determined by the CEPR using the euro area real GDP. MU dates are turning points identified by the Bry-Boschan algorithm when applied to the Moench/Uhlig (MU) monthly series of euro area real GDP.

* The end of the last recession period that started 2011:07(q3) was not determined considering the sample period.

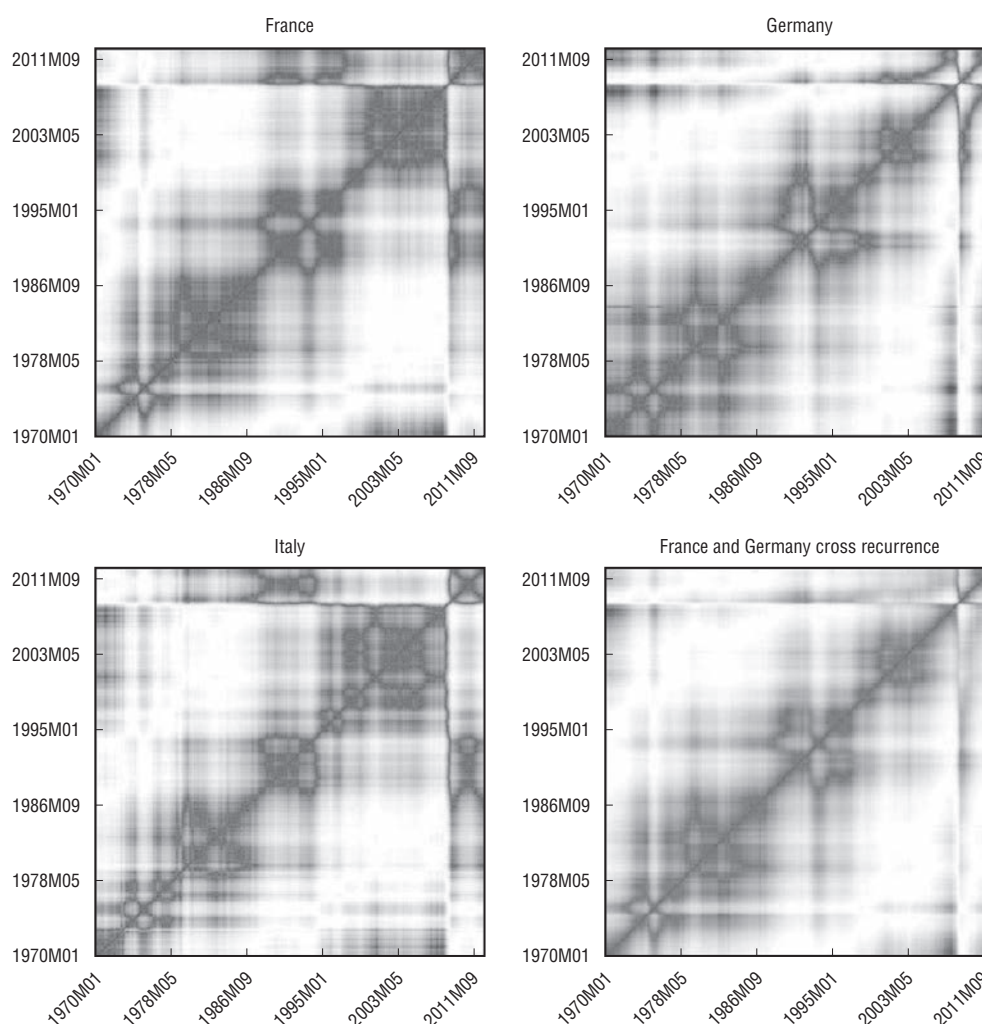
4. Conclusion

In this work, we have demonstrated the usefulness of recurrence plots in identifying, dating and explaining economic crisis. The study provides a preliminary exploratory analysis of the US business cycle to validate the procedure and to apply to the euro area. The findings from the data analysis with recurrence plots, in this case referred to as distance plots, shows that these plots are robust to extreme values, non-stationarity and applicable to both short and long-term data. This approach is also replicable and transparent, and is adaptive to any time series. In particular, we show that this approach provides a transparent chronology of business cycles since it avoids revision of crisis dates

Figure 5. **Distance plots of the US IPI and euro area IPI, 1991:07**Figure 6. **Cross recurrence plot to visualise the simultaneous occurrence of a similar state in both the US IPI and euro IPI**

through time. The proposed methodology can easily be used in dating business cycles in country-specific time series for the European economies. Obviously, the nature of the distance plots will depend on the underlying economic indicator(s) of the given country as displayed in Figure 7. Finally, a direct extension of this paper would be to consider the use of joint recurrence plots on multivariate time series (for example, production, employment, real income and real sales), which in this case will be a vector of indicators.¹²

Figure 7. **Distance plots of the monthly IPI series of selected European countries: France, Germany and Italy, 1970:01 to 2012:11**



Source: Billio and Casarin (2010) and Eurostat.

Notes

1. For more information on announcement of these dates, see www.nber.org/cycles.html.
2. A comprehensive introduction and bibliography about on recurrence plots is available on www.recurrenceplot.tk/ and Marwan et al. (2007).
3. Phase spaces are usually high-dimensional which makes it difficult to visualise. Eckmann et al. (1987) introduction of the recurrence plot enables us to investigate the m-dimensional phase space trajectory through a two-dimensional representation of its recurrences. This is interesting as

higher-dimensional phase spaces can only be visualised by projection into the two or three-dimensional sub-spaces.

4. The state of a system typically changes in time, and, hence, the vector in the phase space describes a trajectory representing the time evolution, the dynamics, of the system. This trajectory is referred to as a phase space trajectory (Takens (1981; Kantz and Schreiber (1997)).
5. For more details on these variations, we refer the reader to www.recurrence-plot.tk/variations.php.
6. It is same unit since both univariate time series are indexes.
7. The small-scale structures as in single dots, diagonal lines and vertical or horizontal lines. These can also be extended clusters resulting from a mixture of the latter.
8. The distance plots are generated with the Cross Recurrence Plot Toolbox in Matlab provided by Norbert Marwan upon request: <http://tocsy.pik-potsdam.de/CRPtoolbox/>.
9. The data can be downloaded from Federal Reserve Bank of St. Louis.
10. www.nber.org/cycles.html.
11. The size refers to the length in time from the start and end on the formation of butterfly-like structure along the main diagonal.
12. The NBER provides a chronology of the classical business cycle for the US, based on the consensus of a set of coincident indicators which are widely accepted among economists and policy makers. See www.nber.org.

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Report

Russian cyclical indicators and their usefulness in real time: An experience of the 2008-09 recession

by
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This report investigates the predictability of cyclical turning points in Russia. For years, anyone interested in Russia had access to a full set of common tools for business cycle analysis, such as several composite leading indicators, a purchasing managers' index, enterprise and consumer sentiment indexes, and so on. However, the 2008-09 world financial crisis spread throughout Russia quite unexpectedly for most politicians, businessmen and experts alike. Is it possible that none of existing indexes were able to say anything about the approaching decline? Using a simple "rule of thumb" proposed in this report one may easily see that that in reality this was not the case. So then why did a more or less definite forecast provided by some indexes have no consequences for common economic sentiments in Russia? This report gives some answers to this question.

Keywords: recession; growth cycles; cyclical indicators; leading indicators; turning points; Russia

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1. Introduction: Was the last recession expected in Russia?

The first signs of financial turbulence in the world economy became apparent in August 2007; the lowering of interest rates by the US Federal Reserve System (FRS) began in September 2007. December 2007 was, as we now know well, the last month of growth before the Great Recession of the US economy. The US and global crises were readily recognised in Russia, but almost nobody saw any substantial risk for Russia itself. For example, on January 23, 2008, Alexei Kudrin (the Russian Finance Minister), in his interview which was taken during the World Economic Forum in Davos, said:

“In the past few years, Russia has managed to achieve economic stability piling up substantial international reserves, which play the role of an airbag. I believe Russia will soon be the focus of attention as a haven of stability... As a country with substantial reserves, Russia could help soothe the global crisis”.¹

The idea of Russia as “a haven of stability” was not only the manifestation of an “official” over-optimism, but became very popular among Russians. As the exchange and interest rates remained stable and the value of international reserves continued to grow, the common opinion was that Russia would be quite resistant to the turbulence in the world economy.²

The unexpectedness of a deep recession in Russia was even more surprising since for years anyone interested in the subject had had access to a full set of tools for business cycle analysis, such as several versions of a composite leading index, a purchasing managers’ index, an enterprise sentiment indexes, and so on. Is it possible that none of the existing indexes were able to say anything about the approaching decline? In reality, this was not the case. So then why did all this information have no consequences for common economic sentiments in Russia? We may find several reasons for this.

First, during a long period of more or less monotonic economic expansion (which began after the crisis of 1998) there were but a few chances to calibrate leading indexes for their real leading qualities. So, when some of them began to signal future decline (the various indexes actually did this with variable clarity) there was no reason to trust any particular indicator more than the other.

The second reason has to do with more than just a formal statistical criterion. Contemporary economic life is measured in days and hours, but most usual economic indicators have inevitable lags of months and sometimes quarters (such as GDP). Moreover, the real-time picture of economic dynamics may differ in some sense from the same picture in its historical perspective (because all fluctuations receive their proper weights only in the context of the whole). Therefore, it is important to understand if monthly leading indicators really are capable of providing important information on Russia to decision-makers.

Now, several years after the last recession (and with the potential for new crises), it is time to compare the predictive powers of various Russian cyclical indicators and choose

the best ones. The main question for us can be formulated in the following way: “Was it actually possible to predict a turning point relying on the dynamics of one or another leading indicator?”

The next part of the report briefly describes all leading indexes available in Russia. Then methodological approaches to detecting turning points in real time are discussed, literature is surveyed and a simple “rule of thumb” for comparisons of various cyclical indicators is suggested. The main indexes’ predictive power is discussed afterwards. The final section outlines the usefulness of various cyclical indicators in Russia and prospects for their practical use.

2. Data and methods

2.1. Cyclical indicators for Russia

The list of every Russian cyclical indicator ever proposed is shown in Annex A. A brief overview of this information suggests that only the first five out of 14 cyclical indicators are meaningful for evaluation and comparison with one another. One indicator is a classical purchasing managers’ index (PMI); one is similar to the European Commission’s confidence index; and, three [including two by the Organisation for Economic Co-operation and Development (OECD) and one by the Higher School of Economics (HSE) Development Center] correspond well to the ordinary logic of composite leading indexes (CLIs). All of the others are now not fully suitable for business cycle monitoring simply because there are no available, comparable and regularly published monthly figures for them.

All our considerations are limited to the last crisis, 2008-09. No quasi-real time comparisons for the previous Russian crisis (1998) are meaningful, as in fact three of our five indicators were introduced after 2000, and the methodology for the remaining two has radically changed.

2.2. Dating the 2008-09 recession’s peak and trough

We decided to base our analysis on the classical concept of business cycles, rather than on concepts of growth or growth rates cycles. Hence, ups and downs in Russian economic activity are important for us. As there are no conventional dates for cyclical turning points for Russia so far, we decided to use an index which is coincident with the economic cycle. Four indicators are commonly used for constructing such indexes: a) employees on nonagricultural payrolls; b) real personal income; c) index of industrial production; and, d) manufacturing and trade sales.³ However, there are no statistical data for manufacturing sales in Russia; figures for employment are very unreliable and often could not be interpreted in the short-run; and the real personal income near a trough is highly dependent on the time of devaluation of the exchange rate which to a great extent is defined by Central Bank’s decisions and hence usually lagging (not leading or coincident) the business cycle.

This is why we took the official basic branches’ index as a main coincident indicator for the Russian business cycle. This index is a weighted average of physical output indexes for six sectors: industry, agriculture, construction, transportation, retail trade and wholesale trade. We also tried the industrial production index as an alternative measure of economic activity (a relatively common practice; for example, the OECD uses indexes of industrial output in its well-known research on economic cycles).

As there are no official seasonally adjusted indexes of production in Russia, we made seasonal adjustments ourselves using X-12-ARIMA and TRAMO/SEATS algorithms (as implemented in the program *Demetra*). In order to define turning points of the last recession we used the most simple method (simply taking local maximum as a peak and local minimum as a trough) as well as more sophisticated methods by Bry and Boschan (1971) and Harding and Pagan (2002). But as all of them gave precisely the same estimates for the last recession they are not shown separately in Table 1.

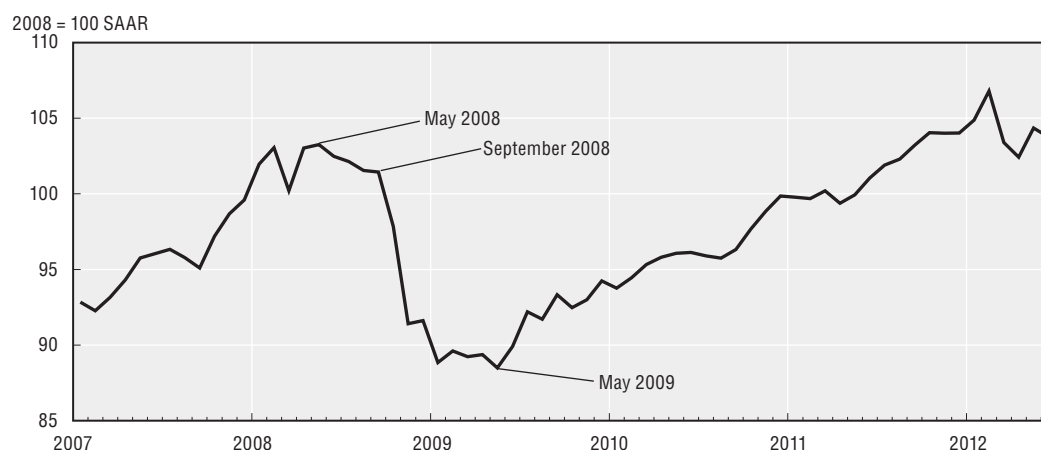
Table 1. Alternative estimates of the turning points during the last Russian recession, 2008-09

Coincident indicator	Methods for seasonal adjustments			
	X-12-ARIMA	TRAMO/SEATS	X-12-ARIMA	TRAMO/SEATS
	The Peak		The Trough	
Basic branches' output	May 2008	May 2008	May 2009	Jan 2009
Industrial production	Feb 2008	Feb 2008	Jan 2009	Jan 2009

Our final choice of the turning points is founded on two practical points. First, we believe that basic branches are closer to the whole economy than industry alone. Second, we think that May 2008 is a better estimate for the peak, because the first contraction of the seasonally adjusted real GDP was observed just in the third quarter of the year (with the peak in February 2008 there would be a GDP decline not in the third but in the second quarter); in a similar way, we think that May 2009 is a better estimate for the trough, because the first expansion of the real GDP was observed in the third quarter of 2009 (with the trough in January 2009 there would be a positive real GDP growth in the first, or at least, in the second quarter). So we chose basic branches' output as the main coincident index; X-12-ARIMA as the main method for seasonal adjustments; and, May 2008 and May 2009 as the estimates of the peak and the trough, correspondingly.⁴ The dynamic of the basic branches' index is plotted in Figure 1.

Figure 1. Output of basic branches, index

2008 = 100 seasonally adjusted at annual rates



Note: SAAR = seasonally adjusted at annual rates.

Source: Rosstat. Seasonally adjusted by the author.

Besides the formal peak in May 2008, one should consider September 2008 as a complementary peak or a “brink of a precipice”. Until now, many have thought that the recession in Russia began only after the Lehman Brothers’ bankruptcy in September 2008. So, the investigation of predictive power of leading indicators ought to be focused not only on May 2008 but also on September 2008.

2.3. Real-time analyses and data vintages

All cyclical indicators are usually revised because of revisions of initial statistical data, re-estimation of seasonal adjustments and general improvement of the methodology. All these reasons are quite natural and hence undisputable; however, they cause a doubling of perception: one view may be visible in real-time (with flash or preliminary data) and a quite different one, in historical retrospective, with revised data and adjusted methodology. Our aim here is to check the real-time qualities of several cyclical indicators during the last recession.

We could not investigate all historical data vintages and all the movements of all available cyclical indicators. This procedure would be too costly and time-consuming. Rather, we analysed only those time-series and vintages which had corresponded to the moments of cyclical turning points. Of course, in real time nobody knew that the recession was just around the corner. But did the indicators tell us that this change was approaching?

One should also keep in mind that information about each month became available one or two months later. For example, until the 20th of October 2008 (which was a crisis month), one could learn only that in August the growth rate of basic branches had risen. And according to the real-time information, it had risen for the second month in a row. This was not a very valuable piece of coincident information for forecasting a recession.⁵

But what did the existing leading indicators show on the eve of the crisis? Were there signs of recession visible in advance or not? The answer to this question is not as simple as it seems, because these indicators, just like all other financial and economic indicators, tend to fluctuate. Therefore, one must decide whether these fluctuations are just white noise or whether they contain an important signal about changes in the trajectory of the economic activity as well. In other words, one must extract middle-run changes in the trajectory of leading indicators resting upon only a few observations.

2.4. Statistical methods used for detecting turning points

There were tens of resourceful researches devoted to cyclical turning points’ dating and prediction. Most of them were based on the US time-series and used, more or less, formal methods including: regression analyses; spectral analyses; dynamic factor model; principal components; VAR in its various modifications; macroeconomic models; various statistical diagnostics rules adapted from engineering, informatics, biology, medicine and other sciences (including even from earthquakes forecasting); Markov regime-switching models; various modifications of probit and logit models; and, many other methods.⁶

One may argue that econometrical methods are the most promising for forecasting cyclical turning points in Russia, but we do not agree. As a post-Soviet market-oriented Russian economy has a short history (only around 20 years) and as recessions are very rare events, it is difficult to obtain reliable parameters by traditional statistical methods. Furthermore, most of these methods need a true set of peaks and troughs for a historical learning period, but there is no such set in Russia. Strict econometrical methods are the best for countries such as the USA who have high quality statistics and, for example, the NBER conventional list of business cycle turning points. But in many other countries

(especially in emerging countries, and Russia in particular) the quality of statistics is much worse, and there are no common views on dating of cyclical turning points. In this situation one may either: a) wait for several decades for better statistics, longer time-series, and an official set of peaks and troughs; or, b) use some simple heuristic methods (rules of thumb) with existing statistics, short time-series and an arguable set of turning points. We decided to follow the second option.

2.5. Rules of thumb: A survey

If an expert intends to compare the behaviour of existing Russian cyclical indicators in real time and to reveal the ones which are possibly useful (by which, we mean useful for decision makers in a highly uncertain situation with unknown or “open” dates of the successive turning points), they have no other way but to analyse very simple statistical measurements of those indicators and then to apply some rule of thumb.

Those measurements found in literature are: a) changes in an indicator’s level over a time span (one or several months or quarters); and, b) diffusion indexes or dispersions of components of the composite indicators.⁷ As we decided to stint ourselves to only analyse the aggregated Russian indexes and not their components, we looked at the measures of change. The rules of thumb proposed before are:

- Two consecutive quarters of GDP decline (2Q). Many have investigated this popular rule and remained unsatisfied;
- Decline after N-months, or quarters, span;
- Two, three, four, etc. months of consecutive decline of a cyclical indicator (2CD, 3CD, 4CD);
- Various kindred rules: two consecutive months of negative and decelerating growth;⁸ a peak for two or more subsequent months; the percentage difference between the current value of the CLI and its maximum value over the preceding 12 months; the percentage gap between the current value of the CLI and a twelve-month moving average of past values, etc.;⁹
- “Accumulated” measures: three-out-of-four months of decline; four out of five months; the percentage of synchronous movements (movements in the same direction) for a target indicator and predictors of this indicator, etc.;¹⁰
- The “3D” rule: the duration, depth and diffusion for recent moments in comparison with their historical standards;¹¹
- Other thresholds’ rules, for example 50% for PMI.

The main shortcomings of the most popular rules are well-known. All quarterly rules are not suitable for real-time analyses simply because of low frequency and large publication lags. The “number of consecutive months of decline (NCD)” rules generate false signals too often if N=2 or 3; more prolonged periods of uninterrupted decline (growth) are very rare, and hence this rule may generate a lot of missed turning points. Lastly, the 3D (duration, depth, diffusion) rule is not applicable to our multi-indicators real-time analyses for Russia because of: a) a short history of many new leading indicators; b) important methodological revisions for some old indicators; and, c) a short history of business cycles movements *per se*. All these factors hamper statistical estimation of thresholds for each “D”.

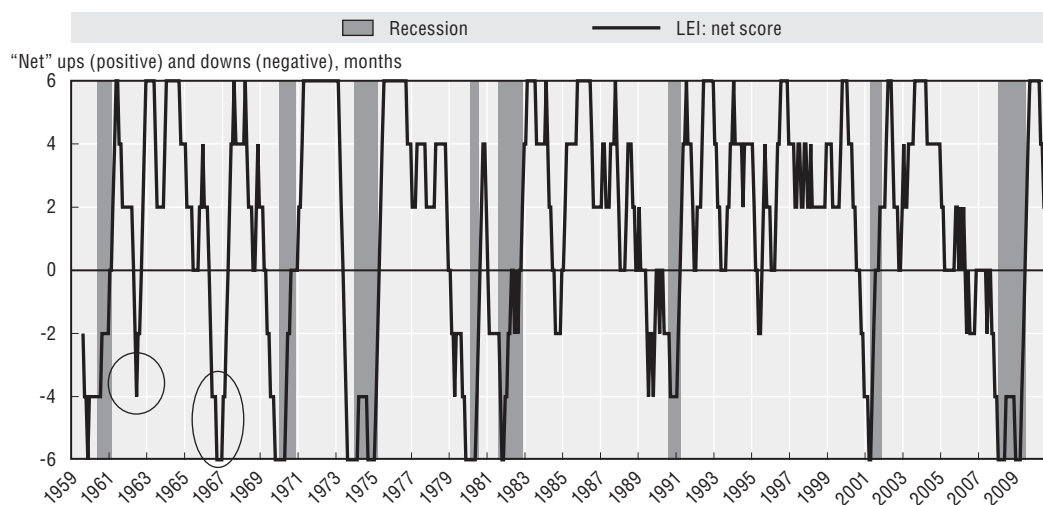
2.6. Our rule of thumb

As was stated above, we need to extract the middle-run changes in cyclical waves resting upon only a few observations. Fortunately, we do not need to predict the exact moment of a turning point in real time; rather we have to reveal a change in the cyclical trajectory to the opposite direction. Many authors assume (and we agree), that the minimum time span that is required before we may speak about cyclical decline (growth) is six months. We assume that a negative/positive cyclical wave is under way if a cyclical indicator is declining/growing in five (minimum) months out of six. On these grounds, we propose a new rule of thumb for detecting cyclical turning points in real time.

Designating a negative monthly change with -1 and positive monthly change with +1, we may affirm that the sum for a six months span would be between -6 and +6. If all six changes have the same sign, the sum is equal to -6/+6; if only five changes have the same sign and one change has another sign the sum is equal to -4/+4. If the sum is -2, 0 or +2, we may conclude that no definite direction is observed.

The result of an application of this rule to the well-known leading economic index (LEI) by the Conference Board and the NBER set of turning points is wholly satisfactory (see Figure 2).

Figure 2. “Five out of six” rule applied to the Conference Board’s leading economic index



Note: LEI = leading economic index.

Source: The Conference Board; NBER. Author's calculations.

For more than the last 50 years, there were eight recessions in the USA. Our rule gave no missed signals and only two false signals for the period. In both cases of false signals (1962 and 1966), one could observe a sharp decline in growth rates and massive introduced stimulation measures. So both signals were not absolutely false. As for after-crisis expansions, in all eight cases the net score was more than -2 (which means no tendency to decline) at least at the trough and usually several months earlier. Of course, this does not prove that our rule is good, but rather that the LEI by the Conference Board is good.¹² But this is just what we need: to have an instrument to differentiate between “good” and “bad” indicators.

For the subsequent comparisons for Russia, we decided to count a net number of months (from a six-month span) when a cyclical indicator changed in proper direction (down before a peak and up before a trough). We assumed that an indicator with a high absolute score on the eve of a turning point had some anticipatory trend in proper direction and possibly useful for predictions in real time. On the contrary, an indicator with a low score showed only chaotic oscillations and hence was rather useless for predicting a turning point.

3. Did the leading indicators signal in advance in Russia?

3.1. One more preliminary remark

All real time vintages exist only for both OECD indexes. The PMI by Markit Economics and the ICI by HSE were not revised during our period. Knowing the release dates for these indicators, it is easy to reconstruct their exact real time values on the base of the current time-series. The situation with the CLI by the Development Center is, to some extent, worse because there is no archive with real time vintages; only the last version of the whole time series exists. The revisions of the CLI were dependent on corrections of data from the used survey of Russian enterprises. As these revisions usually affected only one month and were not too large, we used quasi-vintages for the CLI by the Development Center. We hope that this didn't distort our final qualitative conclusions.

3.2. Predicting the peak and “brink of the precipice” of May and September 2008

Applying the proposed rule of thumb to the Russian economy, we first have to state that no indicator existed in Russia that could forecast the formal peak (May 2008) in real time (see Figure 3 and Table 2).¹³ The most definite signal for the brink of the precipice (September 2008) in real time was produced by the purchasing managers' index (PMI). The economy was in decline since February 2008 and after June, the negative tendency became quite clear. In August to September, the Markit PMI fell below 50, a level that is usually considered as critical.

A composite leading index (CLI) by the Development Center (DC) dropped into the negative territory in September and this was the seven-year minimum. On the other hand, the recession was still doubtful as there was no recession in Russia seven years ago.

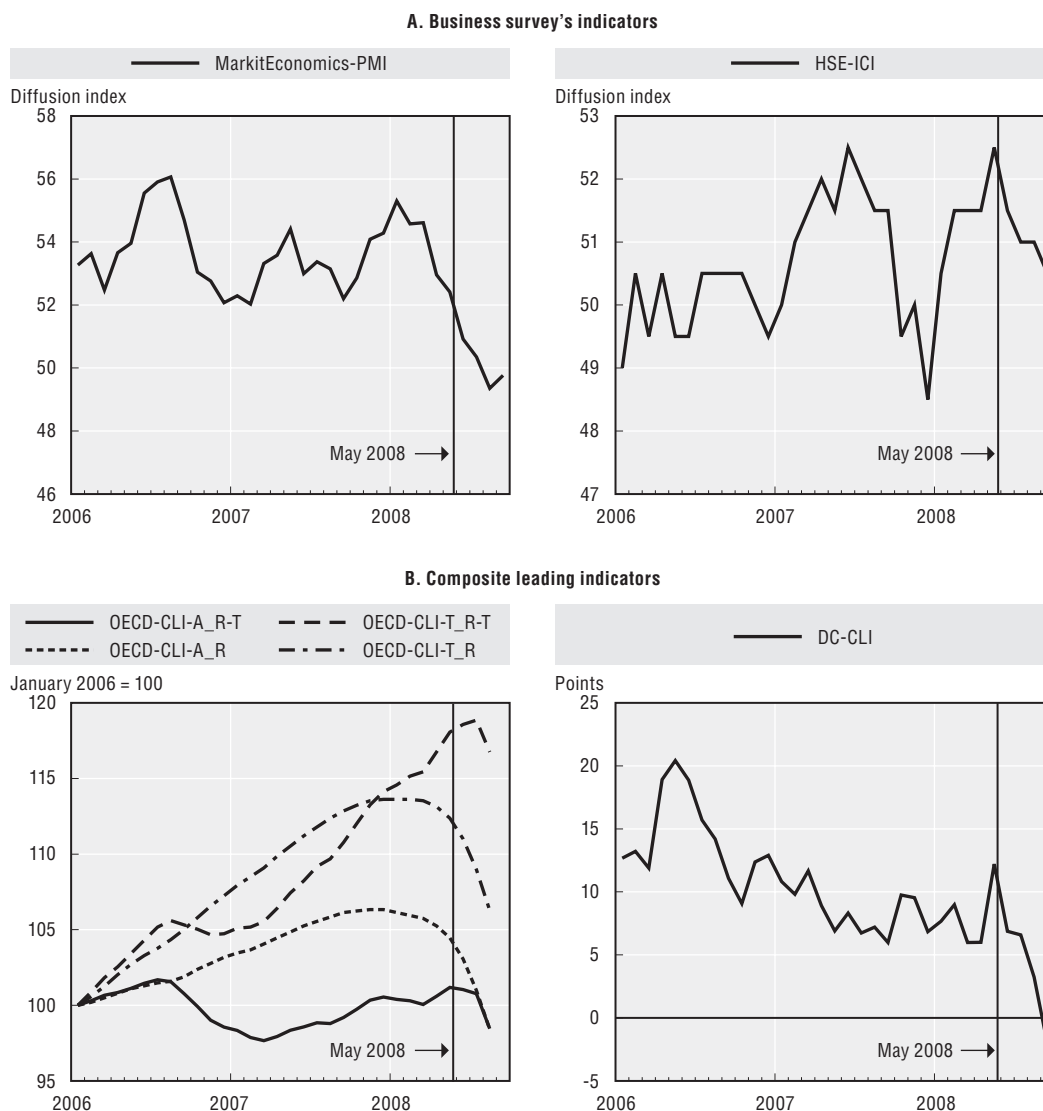
The situation with Industrial Confidence Index (ICI) by Higher School of Economics (HSE) was even worse: the index fell for several months before September but the amplitude of these fluctuations was quite ordinary and gave no reasons to forecast the beginning of a recession.

Finally, the OECD composite leading indexes (CLI) were useless in real time; both in amplitude adjusted, and in trend restored forms. Rather, they pointed to a growth, not decline, of the economy. Note, that the opposite is the case for the revised CLIs. One may guess that the radical revision of the OECD CLI for Russia made in February 2010 (it included a new set of components) was the main cause of the improvement.

3.3. Predicting the trough of May 2009

Now it is easy to verify that most of the leading indicators began to grow in December 2008 or January 2009, but one or two months of growth were not enough to forecast the end of the recession.¹⁴ The situation became clearer by May 2009. The PMI by Markit Economics, the CLI by the DC, and the ICI by HSE all gave more or less clear signals for the

Figure 3. **Russian cyclical indicators as they were on the threshold of the peak and “brink of the precipice” (May and September 2008)**



Source: A. Markit Economics; Higher School of Economics (HSE). B. OECD; Development Center (DC). See Annex A for further details.

forthcoming trough in real time (see Figure 4 and Table 3). The most definite warning came from the CLI by the DC, but the PMI by Markit Economics and the ICI by HSE were also acceptable. This cannot be said for the CLIs by the OECD, in real time the CLIs pointed to a further decline of the Russian economy, rather than to its bottoming.¹⁵

3.4. Why did the experts recognise cycle turning points in real time so rarely?

The main finding from the previous section is that some cyclical indicators more or less gave important signals about the approaching turning points in real time during the 2008-09 recession but those signals were, for the most part, not entirely definite. This is not a surprise. A deterioration, which afterwards could be easily recognised as the first sign of the last recession, in real time could look like an insignificant fluctuation of current economic conditions. So, some final diagnosis was needed by an expert who could weigh

Table 2. **Net score of ups and downs on the threshold of the “brink of the precipice” (September 2008, a 6 month span)**

Indicator	R-T publication date	Net score		Analysis
		R-T	R	
Business surveys' indicators				
Markit-PMI	01/10/08	-4	NR	In real time, this indicator gave a serious signal for the beginning of the recession. Although the net score for September 2008 was equal only to -4 one could observe a clear tendency for the declining after January 2008. Besides, in August 2008 the index dropped below the critical 50% level for the first time since November 2004. There was no alarm signal in May 2008 as fluctuations were inside the usual range.
HSE-ICI	07/10/08	-4	NR	Although the net score for HSE-ICI is -4 in September 2008, it is difficult to imagine that somebody could insist that this indicator predicted an inevitable recession; its drop at the end of 2007 was more impressive but the Russian economy continued to grow. In May 2008, the ICI pointed to an accelerating of the economy rather than to its slowdown.
Composite leading indicators				
DC-CLI	20/10/08	NA	-2	Net score for the index is only -2, but the DC-CLI has dropped for the last four months since June 2008 and in September, its level was at a minimum for seven years. So one could suppose that some serious problems for Russian economy are on the way. The dynamics of the index in May gave no signs of such risks.
OECD-CLI-A	10/10/08	-2	-6	The real-time net score for the OECD-CLI-A for the “brink of the precipice” is quite low. It is even worse for the “formal peak” of May 2008. Visual analysis easily confirms that there was no useful signal from the indicator in real time. The picture became radically different after revisions. The net score for the revised OECD-CLI-A is equal to -6 (the possible minimum) for September 2008 and gives strong signals for May as well.
OECD-CLI-T	10/10/08	+4	-6	The general picture for the OECD-CLI-T is the same as for the OECD-CLI-A: no useful signal in real-time, and a very strong and clear signal after revisions. Note that the net scores for all OECD indicators were calculated using the last point available in real time. Usually the publication lag for these indicators has one additional month in comparison to all other indicators.

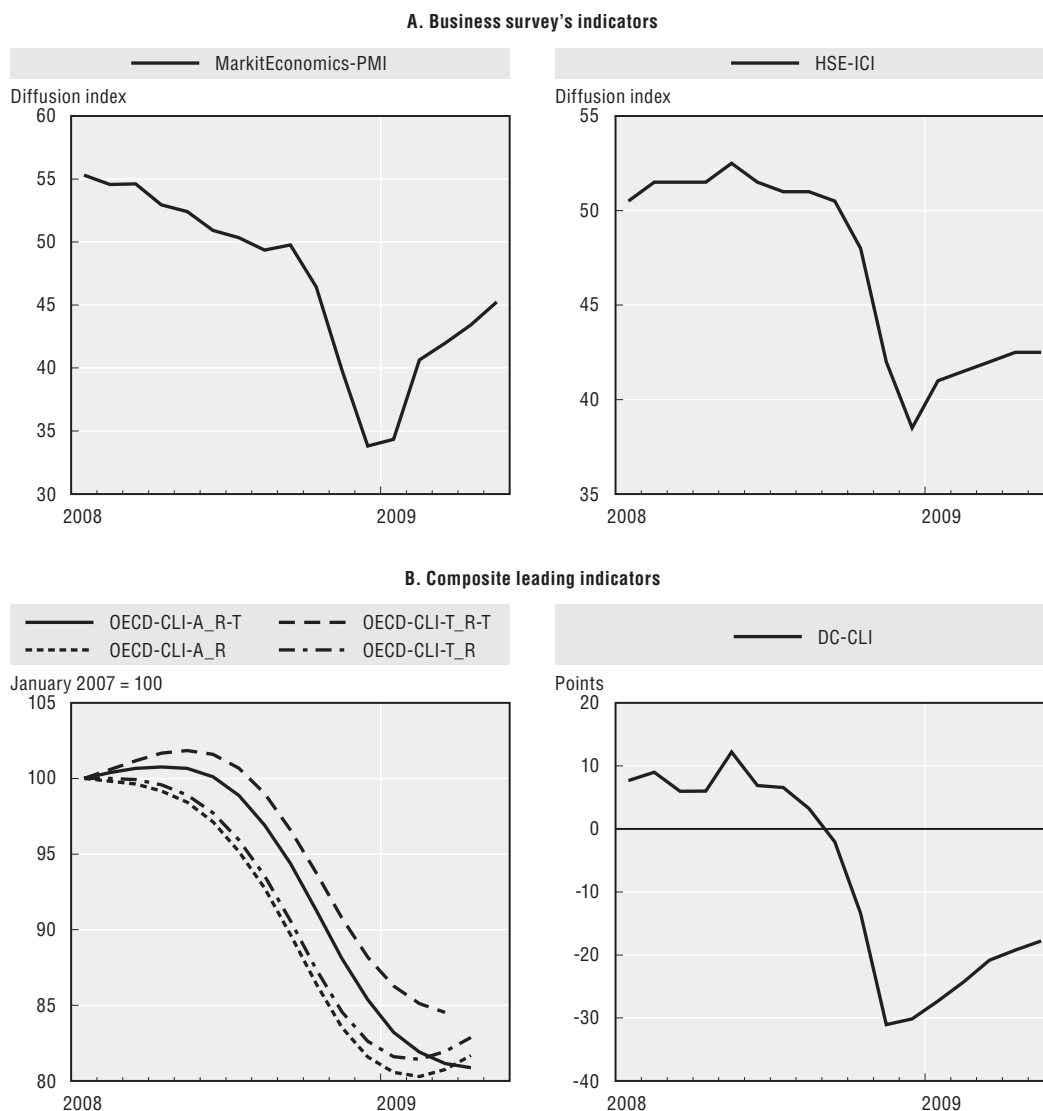
Notes: NA – not available; NR – no revisions; R-T – real time (October 2008); R – revision of January 2011. A negative net score means that the number of downs – during a 6-month span before a turning point – is greater than the number of ups; for a positive score the opposite is the case.

all the pros and cons, and propose their personal conclusion. But if one remembers what the experts told us in real time, one would probably be surprised by the high degree of an experts' caution. For example, the experts usually predicted the slowing of growth just before the drop of the economy (see Table 4).

This result is not specific to Russia. For example, Fels and Hinshaw (1968, p.30) wrote “many were noncommittal, others optimistic” about the 1957 peak in the USA; and, Fintzen and Stekler (1999) have studied similar issues for the 1990 US recession. One of the possible explanations of the failure of predicting recessions is a “wishful bias”: experts do not forecast recessions because nobody (including themselves) wishes them to begin.¹⁶ The experts hope to the last and admit that there is a recession only after it has begun instead of predicting it. This may be true in spite of quite visible signals from the cyclical indicators in real time and we suppose that this was the true for Russia during the last recession.

One may also notice from Table 4 that in Russia an excessive optimism just before the recession was almost as equally widespread as an excessive pessimism just before the recovery. This result is quite surprising because many authors have noted that it is less difficult to predict the end of a recession than to predict its beginning (Fels and Hinshaw, 1968; Hymans, 1973; Chaffin and Talley, 1989; Koenig and Emery, 1991 and 1994; Fintzen and Stekler, 1999; Anas and Ferrara, 2004). Why is this not the case in Russia? Our hypothesis is that the history of Russian business cycles (and hence of business cycle

Figure 4. **Russian cyclical indicators as they were on threshold of the trough (May 2009)**



Source: A. Markit Economics; Higher School of Economics (HSE). B. OECD; Development Center (DC). See Annex A for further details.

indicators) is too short and because of this, experts have too little experience in interpreting their data. In these circumstances they have a spontaneous propensity for extrapolation of the current situation in their comments and rarely have enough courage to forecast a radical change of tendencies, even if their indicators point to this change.

Table 3. **Net score of ups and downs on the threshold of the trough (May 2009, a 6 month span)**

Indicator	R-T publication date	Net score		Analysis
		R-T	R	
Business surveys' indicators				
Markit-PMI	01/09/09	+4	NR	In real time, the indicator gave a serious sign for the end of the recession: it began to grow in January 2009 and since then it has risen continually for five months.
HSE-ICI	07/06/09	+4	NR	The net score for HSE-ICI is +4 in May 2009. Hence, the end of recession (the trough) in the near future is quite plausible.
Composite leading indicators				
DC-CLI	15/06/09	NA	+6	Net score for the index is +6. The signal for the forthcoming trough and the subsequent growth is as large as possible.
OECD-CLI-A	08/06/09	-6	-2	The real-time net score for the trough of May 2009 is equal to -6 (the possible minimum for a six-month span). It means that this indicator gave a definite signal of the opposite sign. After revisions, a trough was revealed in the trajectory but the ascending segment of the time series is too short to detect the trough with confidence.
OECD-CLI-T	08/06/09	-6	-4	The general picture for the OECD-CLI-T is the same as for the OECD-CLI-A (see also the notes for this indicator in Table 2).

Notes: NA – not available; NR – no revisions; R-T – real time (October 2008); R – revision of January 2011. A negative net score means that the number of downs – during a 6-month span before a turning point – is greater than the number of ups; for a positive score the opposite is the case.

4. Conclusions

First, we may state that during the 2008-09 recession, some cyclical indicators could be really useful in foreseeing turning points in real time, as it may be caught by the “five (minimum) out of six” rule of thumb which indicates that they have changed their trajectories in the opposite direction some months before a turning point. We hope that in the future our rule of thumb may be useful for experts and policy makers while also detecting cyclical turning points in real time.

Second, according to the proposed criterion, the PMI by Markit Economics and, to some extent, the CLI by the Development Center, both could be quite useful. The usefulness of the ICI by HSE is less obvious.

A few more words should be said about the CLIs by the OECD which were not good enough for Russia. The most obvious explanation is that the old composition of components of the aggregated index was not relevant. But we want to underline one more point. The statistical procedure used by the OECD supposes intensive smoothing of the initial data. It is quite acceptable for developed countries with their well-established processes and stable inter-relations. But it is possibly inconsistent with the unsettled and highly variable character of the Russian economy.¹⁷ In our research the CLIs by the OECD for Russia turned out to be over-smoothed, and hence, gave no important information for detecting turns near the end of time-series. On the other hand, the OECD indicators may become more precise as time goes on, the time-series get longer and the Russian economy becomes more stable.

Third, a prominent alarm signal from the leading and other cyclical indicators hardly leads, but rather coincides. This is not bad, however. Geoffrey Moore in 1950 wrote, “if the user of statistical indicators could do no better than recognise contemporaneously the turns in general economic activity denoted by our reference dates, he would have a better record than most of his fellows” (Moore, 1961, p.76). Several other well-known researchers

Table 4. **News releases for various cyclical indicators in real time**

Indicators	R-T publication date	Diagnosis in real time	Notes
The peak (May 2008)			
Markit- PMI	02/06/08	"... the slowest improvement in business conditions since last September [2007]."	The improvement in business conditions, while the slowest for several months, is an expansion of the economy, not a contraction or recession.
DC-CLI	18/06/08	"With the current level of oil prices, positive dynamics of Russian economy is the only realistic scenario. Some signs of acceleration of internal demand point to the possibility of further increase in GDP growth rates."	The maintenance of positive dynamics (and even some acceleration) is considered as the only realistic scenario. High growth rates of internal demand are not considered as a prerecession overheating.
OECD-CLI-A	06/06/08	"Slow expansion" (April is the last point).	Expansion (although slow) is not a downturn in any sense. Too much optimism.
The brink of the precipice (September 2008)			
Markit-PMI	01/10/08	"PMI data... pointed to a further deterioration of business conditions faced by Russian manufacturers in September, but there were signs of possible improvement in Q4 as new orders rose compared to August and input price inflation continued a downward trend. The headline Russian Manufacturing PMI registered 49.8, indicating a very slight contraction of the sector."	The deterioration of business conditions is stated but it is taken as something temporary. Some signs of improvement in the nearest future are (wrongly) perceived. Now it seems too optimistic, especially as PMI had fallen for eight months until that moment.
DC-CLI	20/10/08	"It is too early to talk about the inevitability of a cyclical crisis (decreasing of output) but an appreciable deterioration of business conditions in real sector appears to be inevitable."	The risk of a recession does not appear to be very high. Scenario of low growth rates is considered to be more probable.
OECD-CLI-A	10/10/08	"Downturn" (August is the last point).	According to the OECD terminology, "downturn" means that the amplitude adjusted CLI is decreasing but its level is still above 100 (long run average). In other words OECD talks about decline of growth rates not decline of total output.
The trough (May 2009)			
Markit-PMI	01/06/09	"Although the rate of decline in manufacturing slowed further in May, the sector is still experiencing a longer and more pronounced contraction than that seen during the financial crisis of 1998".	Although PMI has risen since January it is still below 50% level (45.3% in May). Since then they've talked about less intense contraction but not about the forthcoming growth.
DC-CLI	15/06/09	"To the moment we can only talk about slowing of decline, not about the beginning of the phase of cyclical growth."	The outlook is too pessimistic. In a month's time, an increase of economy will begin, not only the reduction of rates of decreasing.
OECD-CLI-A	08/06/09	"Strong slowdown" (April is the last available point).	According to the OECD terminology, "slowdown" means that the amplitude adjusted CLI is decreasing below 100 level (long run average). In other words, OECD talks about "strong" decline of total output. This was the case in the beginning of the year but in the nearest future an economic recovery will begin.

Note: No available news-releases for the ICI-HSE exist until September 2009

have reached the same point in the past (see for example, Moore, 1961; Fels and Hinshaw, 1968; Greenspan, 1973; Chaffin and Talley, 1989; Koenig and Emery, 1991 and 1994; Lahiri and Wang, 1994; Layton, 1997; Fintzen and Stekler, 1999; Layton and Katsuura, 2001; Peláez, 2005; Hamilton, 2011). Our results confirm that in real time, an alarm signal which is synchronised with an approaching recession is the maximum which one could hope for. It seems that this is a weak result; but one may derive an important practical conclusion from it because not only leading but also coincident cyclical indicators may be suitable for

turning points detection in real time. The only critical condition here is the small publication lag for an indicator (the PMI is an example of such an index).

Finally, while a hypothesis of a wishful bias (which implies that most private experts avoid becoming messengers of bad news) is quite relevant in explaining the failure in forecasting the cyclical peak (and the brink of the precipice), it is not sufficient to explain the failure in forecasting the trough. Rather, Russian experts are too fond of extrapolations, even if some signs of turns exist. In any case, it is evident from all this that the forecasting of cyclical turning points is dependent not only on objective data and methods, but also on subjective conclusions of experts and decision makers.¹⁸ Experts' experience and their forecasting strategies may be of no less importance than the kind of formal methods and instruments they use.

Notes

1. <http://en.rian.ru/russia/20080123/97602999.html>.
2. One may make certain of it by looking through archives of the leading Russian business media (for example, see the weekly journal "Expert" or the daily newspaper "Vedomosti").
3. For example see coincident indexes by The Conference Board.
4. Recall that in May 2008, the index level is only 0.2% higher than in February 2008 and the index level in May 2009 is only 0.4% lower than in January 2009. Therefore, some uncertainty in the dating of turning points definitely exists. In addition, using similar (but not identical) procedures by Belyanova and Nikolaenko (2012) placed the peak of industrial output in July 2008 (they didn't date the trough). The OECD (2012) gives April 2008 as the peak and June 2009 as the trough of the growth cycle (not a classical business cycle). One may only dream about a council of qualified experts that will take responsibility for dating Russian cyclical turning points just as the dating committees of the US National Bureau of Economic Research (NBER) and the Centre for Economic Policy Research (CEPR) in the Eurozone do.
5. The revised data on basic branches' output point to declining growth rates in June-August 2008.
6. See Smirnov (2011), pp. 8-10 for a survey.
7. The second approach is more typical for early papers published in the fifties-sixties of the last century but recent papers by Stock and Watson (2010a; 2010b) with their "heat charts" also belong to this tradition.
8. Statistical data on growth rates for three consecutive months are needed to be aware that those rates have declined at decelerating rates for two consecutive months.
9. Zarnowitz and Moore (1982) supposed to monitor sequential signals of recession and recovery generated by a pair of indexes: leading and coincident growth rates. It is a good idea, but it had no followers for more than 30 years.
10. In general form this non-parametric measure of synchronisation was introduced in Pesaran and Timmermann (1992).
11. For the USA, the "3-D rule", in its up-to-date form requires: a) the six-month growth rate (annualised) of the CLI to fall below minus 3.5%; and, b) the six-month diffusion index to fall below 50% (see, The Conference Board (2001)). However, all the figures (-3.5%, 50%, 6 months) are retrieved from historical dynamics, they are not the global constants. There were other thresholds for 3-D in Shiskin (1974).
12. One should keep in mind that our calculations rest not on real-time but on revised time-series of the Conference Board.
13. We used the following notations there and hereafter: OECD-CLI-A – the OECD index in amplitude adjusted form; OECD-CLI-T – the OECD index in trend restored form; R-T – real time (October 2008 or June 2009) level of all indicators; R – revised time-series (as of January 2011).
14. If one would date February 2009 as the cyclical trough, then he must conclude that no leading indicator gave any help in forecasting the new expansion.

15. The picture changed significantly after the revision in February 2010, but the question about the OECD CLIs for Russia is still open (for example the revised indexes did not give proper signals for deceleration of the growth in 2010q2-q3).
16. Ito (1990) was the first to write about wishful bias in forecasting. He revealed that the forecasters working for Japan's importers predicted statistically stronger exchange rates for the yen than the forecasters working for its exporters (a strong yen is an advantage to Japan's importers, not to its exporters).
17. And maybe of some others emerging countries?
18. Berge and Jordà (2011) wrote: "Agents facing different preferences and constraints will make different decisions from the same reading of an index" (p. 275).

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ANNEX A

Composite cyclical indicators for Russia: A full spectrum

Indicator	Producer	Comments
Purchasing Managers' Index (PMI)	Markit Economics	No revisions since January 2004.
Industrial Confidence Indexes (ICI)	Higher School of Economics (HSE)	Regular news releases only since September 2009. For straight comparability with PMI we transformed it from a balance to a diffusion index according to the formula: $DI = (100+B)/2$
Composite Leading Index (CLI) a) Amplitude Adjusted & b) Trend Restored	Organisation for Economic Co-operation and Development (OECD)	New methodology since December 2008. Additional revision in February 2010.
Composite Leading Index (CLI)	Development Center (DC)	Only in the form of Y-o-Y percentage changes exists. No revisions of methodology since January 2008.
Composite Leading Index (CLI)	Institute of Economy (IE), Russian Academy of Science	Figures never published.
Industrial Confidence Indexes (ICI)	Rosstat	Too short comparable time-series. Cyclical trajectory is quite similar to ICI by HSE.
Industrial Optimism Indexes (IOI)	Gaidar Institute for Economic Policy (IEP)	Introduced in October 2008 and discontinued in November 2010. Current figures are not available regularly.
Leading GDP Indicator	Renaissance Capital - New Economic School (RenCap-NES)	Too short of a history. The indicator's form (GDP forecasts for a pair of quarters) rules out its usage for detecting turning points.
Business Activity Index (BIF)	"Finance." (a Russian business journal)	Irregular news-releases. Too large of a publication lag (up to three months).
Business Activity Index (The Barometer)	"Business Russia" Association ("Delovaya Rossiya")	Too tangled methodology. Incomparability of neighbouring observations. Short history.
Business Climate Index (BCI)	The Russian Union of Industrialists and Entrepreneurs (RSPP)	Introduced in January 2010 (after the 2008-09 recession).
Leading Index of Financial Stability (LIFS)	Gaidar Institute for Economic Policy & Otkritie Capital (IEP-OC)	Introduced in September 2011 (after the 2008-09 recession).
Business Activity Index	The Russian Managers Association & Kommersant Newspaper (MA-K)	Too tangled methodology. Discontinued in April 2009., renewed in the end of 2010

Source: See Annex B.

ANNEX B

Composite cyclical indicators for Russia: A description

B.1. Internationally accepted indexes for Russia

B.1.1. Composite leading index (CLI) by OECD

The OECD is well known as an authoritative producer of CLI for various countries and regions. Russian CLI is the only one of 42 OECD indexes constructed by unified methodology, which is well documented and does not need any additional description. However, since components of a CLI for each country are different, we will focus on this particular point.

From April 2006, the Russian CLI included the following five components (Nilsson, 2006, p.11):

- Order books in manufacturing: level (per cent balance, sa);
- Stock prices: RTS index (2000 = 100);
- World market price crude oil (2000 = 100);
- Monetary aggregate M2, sa;
- Foreign trade balance (f.o.b – c.i.f.), sa.

We could not find the exact moment when one additional indicator was introduced:

- Level of finished goods stocks (inverted).

In February 2010, the Russian CLI (as well as some others) was revised. First, three of its components were retained, but the last three were replaced by:¹

- US imports from Russia (inverted);
- Production trend observed in manufacturing in recent months (per cent balance, sa);
- Assessment of present level of export order-books in manufacturing (per cent balance).

As a source of BTS data OECD began to use polls by the Institute for the Economy in Transition (IEP) instead of the Centre for Economic Analysis (CEA). Since then the trajectory of OECD Russian CLI has changed significantly. Before this it had changed substantially in December 2008, after modification of the OECD procedure for all CLI calculations (Gyomai and Guidetti, 2008). It had also changed slightly every month as a result of seasonal adjustments and re-estimations with one more observation.

OECD publishes all its CLI between the 5th and 11th of a month, around 35-40 days after the end of the month in question. Russian CLI was released for the first time in April 2006.² Now it is published in two forms: trend restored and amplitude adjusted (an index numbers 2005 = 100 and long-term trend = 100, respectively). Since the end of 2008, the

OECD headline indicator is the amplitude adjusted CLI. It allows to identify four qualitatively different cyclical phases:

- expansion – CLI increasing and above 100
- downturn – CLI decreasing and above 100
- slowdown – CLI decreasing and below 100
- recovery – CLI increasing and below 100.

B.1.2. Purchasing managers' index (PMI) by Markit Economics

Another well-known cyclical indicator is the Purchasing Managers' Index. Markit Economics calculates these indexes for 26 main countries and key regions and Russia is one of them. The method for constructing the indexes is universal for all countries.³ Manufacturing PMI is based on a poll of around 300 Russian purchasing managers from this sector which were asked to compare current situation at their unit with the situation one month before. There are five parameters for comparison:

- new orders received (0.30)
- production/output (0.25)
- employment (0.20)
- suppliers' delivery times, volume weighted (0.15)⁴
- stocks of purchases, in units (0.10).

Based on the answers for each of these questions a diffusion index is calculated as a sum of all positive (improvement/increase) and half of neutral (no-change) answers in percent to the whole number of respondents. After seasonal adjustments, five diffusion indexes are averaged into the composite PMI with the weight shown in brackets. If 100% of the survey panel report an increase, the index would read 100. If 100% reported decrease the index would read 0. Thus, the index equal to 50 corresponds to a "no change" situation in manufacturing, more than 50 – to growth, and less than 50 to a decline in this sector.

A PMI for Services is one more indicator calculated by Markit for Russia. It uses similar methodology though slightly different wording of questions. Also the GDP Indicator is derived from PMI surveys of business conditions in the manufacturing and service sectors of Russia by weighting together the output measures from these surveys.

Manufacturing PMI has been calculated since September 1997, Services PMI and GDP indicator since October 2001. All of these indexes are published monthly: manufacturing PMI – on the first working day of a month following the month under consideration, other indexes on the third and fourth working days. Usually there are no revisions to PMI after first publication.⁵

B.2. Russian indexes for Russia: Composite leading indexes (CLI)

B.2.1. CLI and other cyclical indicators by the Development Center (DC)

The system is based on the concept of growth cycles and includes not only leading, but also coincident and lagging composite indicators as well.

For coincident indicators, indexes of physical output for the following sectors are taken:

- Mining
- Manufacturing

- Agriculture
- Construction
- Freight transportation
- Retail trade
- Paid services.

These industries account for about half of Russia's GDP. The weighted average Y-o-Y percentage changes of these seven indexes can be quite adequately used as the Composite Coincident Indicator (CCI). It is available on a monthly basis with just a three week delay after the end of each month, while GDP is calculated only on a quarterly basis and has a two or three month lag after the end of each quarter.

For leading indicators, we use the following seven series:

- Average monthly price of Urals brand crude oil
- The ratio of enterprises facing increased or stable domestic demand (IEP Surveys)
- The ratio of enterprises having no excessive inventories of finished goods (IEP Surveys)
- Nominal money aggregate M2
- The (reverse) index of the real effective exchange rate of a ruble against a basket of currencies of Russia's trade partners (calculated by the Bank of Russia)
- The RTS stock price index
- Interbank interest rates (MIACR-overnight).

The *Composite Leading Indicator (CLI)* is calculated as a weighted average Y-o-Y per cent change of these variables (Y-o-Y differences of some variable is expressed in percent points).

For lagging indicators, we take the following six items:

- Average price of dwelling space per 1 m² in Moscow (in USD)
- Number of imported autos
- Number of officially registered unemployed (in reciprocal form)
- Fixed capital investments
- Credits to enterprises and organisations (as a percentage of total assets of banking sector)
- Foreign currency reserves of the Bank of Russia (excluding gold).

The *Composite Lagging Indicator (CLGI)* is calculated as a weighted average Y-o-Y percentage change of these variables.

The system of cyclical indicators by the Development Center was first introduced in May 2006.⁶ Since then three minor revisions of the methodology took place: one variable was deleted and two replaced by the others.⁷ The indexes are published monthly with average publication lag of 10-15 days for CLI and 40-45 days for CCI and CLGI.

B.2.2. CLI by Institute of Economy (IE), Russian Academy of Science

Similar system of indicators was suggested by authors from Russian Institute of Economy at the very end of 2009.⁸ The leading index from this system is most similar to DC version of CLI: the difference is in one missing variable (inventories in finished goods) and

two additional variables (new orders and foreign trade balance). At the same time they retained the domestic demand variable which is quite collinear with new orders indicator.⁹

Composite coinciding and lagging indexes are less similar to DC. The coinciding index consists of four components: retail sales; wholesale sales; disposable personal income (all in real terms); number of employees. The lagging index consists of eight components: fixed capital investments; core CPI; credits outstanding; household's deposits; number of unemployed (in reciprocal form); the ratio of enterprises in "good" and "normal" financial conditions (CEA Surveys); inventory/sales ratio in retail trade; CPI in paid personal services.¹⁰

Up until now the IE system of cyclical indicators had a more academic than practical use as values of indexes has never been published – neither in a form of historical time-series, nor as monthly updates.

B.2.3. Leading GDP indicator by RenCap-NES

In December 2009 a new cyclical indicator for Russia was presented by Renaissance Capital (one of the largest Russian investment banks) and the New Economic School (a large private university with tight connections to American and European economic science) (Styrin and Potapova-Krylova, 2009). This monthly leading GDP indicator has two prototypes – Eurocoin and Chicago Fed National Activity Index. Their common general purpose is to construct a business activity indicator using principal components method which is applied to the set of almost "all imaginable" financial, economic, and business surveys cyclical indicators. The basic data set for the RenCap-NES' variable consists of 108 time-series beginning from January 1996.

The RenCap-NES indicator is not a single number for measuring economic activity (like Chicago Fed National Activity Index or Eurocoin) but rather a forecast of real GDP percent change. Each month forecasts for the current and the next quarter are recalculated using the most recent statistics available. These figures are published around the 10th of each month.¹¹

The methodological features (monthly forecasts of not just a single but a pair of quarterly GDP growth rates) makes it difficult to compare its historical track with trajectories of other cyclical indicators.

B.3. Russian indexes for Russia: Indexes based on business tendency surveys

B.3.1. Industrial confidence indexes by Higher School of Economics

The industrial confidence index (ICI) by HSE is often seen as one harmonised with European Commission's methodology (European Commission, 2007). It is based on answers of top managers from about 600 main industrial plants who answer the following three questions:

- How do you expect your production to develop over the next 3-4 months? It will...: Increase/Remain unchanged/Decrease;
- Do you consider current overall demand for your production (order books) to be...?: More than sufficient (above normal)/Sufficient (normal for the season)/Not sufficient (below normal);
- Do you consider your current stock of finished products to be...?: Too large (above normal)/Adequate (normal for the season)/Too small (below normal).

The questionnaire was adapted for Russia by the Centre of Economic Analysis in 1995. This Centre estimated the seasonally adjusted ICI until July 2009. Since August 2009 this project was relocated to the Higher School of Economics.

The ICI equals a simple arithmetic average of balances (differences between positive and negative answers, all in percentage points); the last of three balances is taken with inverted sign. The ICI value more than zero means increase of confidence in industry, value less than zero means decrease of confidence. Theoretically a value of ICI may fluctuate between -100 and +100, when in fact the range is much narrower.

There are similar confidence indexes by HSE for three other sectors of Russian economy (construction, retail trade and wholesale trade) and for the economy as a whole (Economic Sentiment Index) but up until this moment they are quarterly, not monthly. Since then it makes little sense to use them in real-time analyses of business cycle.

The ICI by HSE is published monthly, before the 5th working day of a next month.¹²

B.3.2. Industrial confidence index by Rosstat

In parallel with CEA and HSE during all these years the Russian State Statistical Committee (Rosstat) has been calculating non-adjusted ICI based on the same initial data (technically it is Rosstat who takes this survey). Unfortunately the wholly comparable time-series of this index simply doesn't exist. Currently, one can get only 1997-2011 data from Rosstat's site. They are broken into three pieces because of the changes in classification and aggregation methods.¹³ Comparison of these historic time-series with ICI data by HSE shows that they are quite similar and no important additional information is contained in the Rosstat's indicator.

B.3.3. Industrial optimism index by Gaidar Institute for Economic Policy (IEP)

The IEP has been conducting surveys of industrial enterprises (around 700-800 per month) since March 1992 but introduced its Industrial Optimism Index only in October 2008. Before this they preferred to analyse all variables in the questionnaire separately, without combining them into a single number. The beginning of the most acute phase of the last crisis has changed their minds, as it fuelled common interest for this special kind of statistical information.

The Industrial Optimism Index is calculated as a simple average of four "balances":

- Change of demand comparing with the previous month: percentage growth – percentage decline (sa);
- Demand assessments: per cent above normal + per cent normal – per cent below normal;
- Finished goods inventories: per cent above normal + per cent normal – per cent below normal (with inverted sign);
- Physical output, anticipated changes for the next 2-3 months: percentage growth – percentage decline (sa).

The IOI may vary between -100 and +100. At the moment of introduction it was calculated back up until January 1995. If calculated, (after June 2009 not very regularly) it is usually published after 25th of the current month on the IEP site.¹⁴

B.4. Russian indexes for Russia: Less regular indicators

B.4.1. Business Activity Index by Finance. journal

In August 2005 Russian business journal “Finance.” (with a dot) published its Business Activity Index (BIF) for the first time. Since then this monthly index is published from time to time, most often once per quarter.

The BIF is a weighted average of ten basic indexes (January 1995 = 100). According to authors’ idea five of them are intended to present “supply” conditions and other five – “demand” conditions.¹⁵ The first five are:

- Freight transportation turnover;
- Fixed capital investments, real;
- Number of unemployed (in reciprocal form);
- The ratio of enterprises in “good” and “normal” financial conditions (CEA Surveys);
- New orders.

The second five are:

- Retail sales, real;
- Disposable personal income, real;
- Credits outstanding;
- Households’ deposits in commercial banks;
- Average monthly price of Urals brand crude oil.

The logic of this classification is not fully clear. For example, new orders are ordinarily considered as demand, not supply indicator. Also, indicators that are usually considered as coinciding or lagging are mixed along with leading indicators. That is why one shouldn’t expect *a priori* a high leading quality from BIF.

B.4.2. The Barometer by Business Russia (“Delovaya Rossiya”)

Delovaya Rossiya (Business Russia) is a business association which conducts some PR, charity and special research projects. The Barometer by Business Russia is one of the last ones. Its first results were published at the very beginning of the crisis in Russia in October 2008. Since then, it has published monthly barometers, with a two months lag.¹⁶

The Barometer is a compound average of seven complex indexes each consisting of several components. The complex indexes are (the number of components is in the brackets):

- Index of current situation (6);
- Index of enterprise assessments (4);
- Index of competition intensity (4);
- Index of current costs (5);
- Index of resources limitations (6);
- Index of government’s policy effectiveness (11);
- Index of “grey and black” economy development (5).

The full number of components of The Barometer is forty one and it will take too long to mention all of them.

The only primary source of data for all calculations comes from a survey of industrial enterprises conducted by IEP. It uses ordinary questions from IEP, as well as special questions requested by “Business Russia”. The problem is that in attempts to minimise costs not all special questions are presented in the questionnaire each month; some of them are quarterly, some – semi-annual. That is why not all of The Barometers’ values for consecutive months are strictly comparable with each other.

B.4.3. Business climate index (BCI) by the Russian Union of Industrialists and Entrepreneurs

The Russian Union of Industrialists and Entrepreneurs (RSPP) began to publish its own indicator of business climate since January 2010. It is based upon monthly poll of around 40-60 members of RSPP which are asked 25 questions about overall business activity and business activity at their plants, logistics, relations with other businesses, banks and the government, as well as financial markets, investment projects, etc.

The composite BCI consists of seven components:¹⁷

- Index of activity in the branch of origin;
- Index of logistics and infrastructure;
- Index B2B;
- Index B2G;
- Index of financial markets;
- Index of overall business activity;
- Index of investment and social activity.

Usually, five options for answers are stipulated: “much better” – “better” – “no change” – “worse” – “much worse”. All respondents have to choose one alternative, and then partial indexes are calculated as an average for all respondents:

$$I = 1.0 \times \% \text{ better} + 0.5 \times \% \text{ no change} + 1.25 \times \% \text{ much better} - 0.25 \times \% \text{ much worse.}$$

The composite Business Climate Index (BCI) is a simple arithmetic index of seven partial indexes. For our purposes, this BCI is inappropriate simply because it was introduced after the 2008-09 recession.

B.4.4. Leading index of financial stability (LIFS) by Gaidar Institute for Economic Policy & Otkritie Capital (IEP-OC)

In September 2011, a new leading index of financial stability (LIFS) by Gaidar Institute for Economic Policy & Otkritie Capital (IEP-OC) was published. It is based on the following monetary and financial indicators (in the forms of Y-o-Y or/and M-o-M percentage changes):¹⁸

- Money aggregate M_2 (real);
- Money aggregate M2 to international exchange reserves, ratio;
- Money aggregate M2 to monetary base, ratio;
- Core CPI;
- International exchange reserves;
- Interbank interest rate;
- Real exchange rate to USD;

- Medium-run interest rate on government bonds;
- Long-run interest rate on government bonds;
- The RTS stock price index;
- The MICEX corporate bonds' index;
- The MICEX government bonds' index (RGBI);
- Commercial banks' deposits at the Central Bank plus Central Bank's bonds in the hands of commercial banks.

Currently, this time-series is definitely too short (only one point) to analyse its behaviour in real time.

B.4.5. Business activity index by the Russian Managers Association and "Kommersant" newspaper (MA-K)

From May 2002 until April 2009, the Russian Managers Association and the influential Russian business newspaper *Kommersant* (Enterpriser) published an index of business activity. The methodology of this indicator was quite unusual.¹⁹ The final index had two components: the first (objective index) was calculated as a weighted average of more than 25 indicators from real, banking, financial and household sectors as well as foreign trade; and, the second (business assessments index) came out as a result of special monthly poll of about 100 businessmen from six sectors of economy (industry, construction, trade, banking, transport and communication, and agriculture). There was a separate questionnaire for each sector consisting of 5-9 special questions. The striking peculiarity of this business activity index is an inclusion of some banking indicators. Potentially promising, however the stratification of the samples was not very good. Finally, the MA-K overcomplicated procedure did not prove to be very fruitful and in April 2009 (at the height of the crisis), the project was discontinued.

Notes

1. For historical drift in the list of the Russian OECD CLI components, see: Kitrar et al. (2003), Nilsson and Brunet (2006), Nilsson (2006), OECD (2010).
2. We mean the beginning of regular monthly publications. Very preliminary calculations were first published in 2003. See Kitrar et al. (2003).
3. For details, see Markit Economics (2010).
4. The Suppliers' Delivery Times diffusion index is inverted to move in a comparable direction.
5. This is, in fact, quite surprising as any procedure of seasonal adjustment requires some re-estimations from time to time.
6. See Smirnov (2006). For six years before 2006, a CLI with another set of components had been used.
7. Non-weighted average of three indexes of physical output (for trucks, lumber, synthetic resins and plastics) did not work as a leading indicator and was deleted in January 2008. Average price of domestic car VAZ-2110 charged by five large-scale Moscow dealers (in USD) was replaced by a number of imported autos in December 2007; money aggregate M2X which includes both rouble and foreign currency components was replaced by rouble money aggregate M2 in August 2008.
8. Rayskaya et al. (2009). Note, that these same authors have formerly developed a business activity index for "Fanance." journal (see A.4.1).
9. It may be told that the same factor enters the calculations of the CLI with a double weight. There is nothing frightful in it.
10. It is worth to note that most of the lagging indicators here are the same as the BIF components (see A.4.2).

11. See <http://fir.nes.ru/en/science/Pages/indicator.aspx>.
12. See www.hse.ru/news/monitorings.
13. See www.gks.ru/dbscripts/Cbsd/DBInet.cgi?pl=1255091; www.gks.ru/dbscripts/Cbsd/DBInet.cgi?pl=1255113; www.gks.ru/dbscripts/Cbsd/DBInet.cgi?pl=1266017.
14. See www.IEP.ru/index.php?option=com_bibIEP&Itemid=50&catid=298&lang=en&task=showallbib.
15. See (in Russian) www.finansmag.ru/kif.
16. See www.deloros.ru/main.php?mid=163.
17. See <http://archive.rspp.ru/Default.aspx?CatalogId=8830> and www.ksr-rspp.ru/struct/anketa/1/_40_13.php.
18. See www.iep.ru/images/SEMINARS/indicators_financial_stability-rus.pdf.
19. See www.kommersant.ru/doc.aspx?DocsID=322789.

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The *Journal of Business Cycle Measurement and Analysis* is jointly published by the OECD and the Centre for International Research on Economic Tendency Surveys (CIRET) to promote the exchange of knowledge and information on theoretical and operational aspects of economic cycle research, involving both measurement and analysis.

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