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Forecasting the Growth Cycles of the Turkish Economy

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Forecasting the Growth Cycles of the Turkish Economy

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Abstract

This paper first specifies the medium-term growth cycles for the Turkish economy. The impact of the frequency transformation methods and the time-serious filters on cycles and potential output are discussed. Then a composite leading indicator (CLI) is constructed that is correlated with the third lead of the GDP with a coefficient of 0.9. The CLI signals 11 out of 13 turning points in the Turkish growth cycle in the 1993-2016 period. The CLI is coincident with the remaining two turning points, hence still providing early warning. Within the same period, only two false signals are generated by the CLI. Finally, building on the seminal paper by Neftci (1982), a method for computation of the turning point probabilities is developed. The virtue of the method is that it takes into account the observed deepness and steepness in the series.

Keywords: Filters; Growth Cycles; Composite Leading Indicators; Turning Point Probabilities

JEL classification: E32; E37; E66

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Non-technical summary

There are so many events affecting the economy. Some of these are quite short-lived and their impact dies off by itself, not requiring a policy-action. The impact of some, on the other hand, is only manifested in the long-run. These are also out of the realm of monetary and fiscal policy action and more related to policies affecting the structural, deep fundamentals of the economy. When new data arrives, it is hard if not impossible to tell what it implies about the state of the economy from a medium-term perspective. This paper starts by carefully specifying a methodology to single out the policy-relevant picture of the economy, which is called the growth-cycle of the Gross Domestic Product (GDP).

Defining the growth cycles of the GDP is not enough though, as far as the day-to-day policymaking is concerned. The reason is that the data reflecting the economic activity, that is, the GDP, announced with a significant time delay. For example, in Turkey, the GDP of a quarter is announced usually towards the end of the next quarter. So even if her/his staff carefully provides a policy relevant picture of the economy, a policymaker that needs to act today only has information about the economic activity 1.5 quarters ago, as the GDP reflects the average activity within a quarter. That is primarily why economists have been after finding indicators that could signal the current, and if possible the near future state of economic activity. The second contribution of this paper is to come up with a Composite Leading Indicator (CLI) that can provide information about the current and future state of the economy. My paper is not the first effort in this direction. However, the existing CLIs do not perform well recently, and this situation got even worse with the update on the National Accounts by the Turkish Statistical Institute at the end of the year 2016. The new CLI that this paper construct leads the GDP growth cycle by 3-4 months with a correlation about 0.9. Due to the timing of the data dissemination in Turkey, at the current point in time, the value of the CLI of about 1-2 months ago is available. But the leading property of the CLI enables it to provide not only valuable information about the current state of the economy, but also about the direction that the economy is heading a few months into the future.

It is also quite important from policymakers' perspective whether the current conditions of the economy are to go on for an extended period of time, or are about to come to an end in the near future. For example, suppose that the economy is in a recession currently. It is of great importance to note whether the current CLI implies about the ending of the recession in upcoming months, that is the proximity of a turning point in the growth cycle. To contribute in this aspect, this paper also configures state-of-the-art techniques to calculate the probability that a turning point will occur in the near future. My method takes into account the fact that slowdowns are historically deeper that expansions and the recoveries are usually slower than downturns.

1 Introduction

In the business of policy-making, the timing matters. The decisions have to be punctual, clear from delusions, and based on a perfect mixture of judgment and metrics. It is therefore of utmost importance to the policy-makers to distill endless streams of information, and to the greatest possible extent, have a clear view of the current state of the economy, and the direction that it is heading in the near future. This paper aims to contribute to the "metrics" component of the ingredients of the art of policy making for the Turkish economy.

Our first effort in this direction is to characterize the Turkish growth cycles, because as suggested above, we would like to obtain a summary of the state of the economy at any point in time, as a first step. A natural starting point would be to come up with a benchmark, towards which the current state can be gauged. A strategy similar to the one that is used by the OECD is followed in this regard. Namely, the benchmark will be the long-run stochastic growth rate of the economy, and the current state will be characterized by deviations from this trend, which will be called, using the OECD lexicon, the growth cycles of the Turkish economy. There are many ways to characterize the growth cycles, but the double-HP approach of the OECD is used in this paper with the difference that the selection of the parameter of the filter in our strategy will be dynamic and peculiar to the variable, as we are interested in the medium term picture of the economy, and desire to rivet at this point both from the perspective of the frequency domain and the time domain.

If the transitory shocks are regarded as affecting the potential output, the application of the double-HP filter has the interpretation as a particular distribution of the variation in the GDP series into the cycle and the potential growth rate itself. This interpretation is consistent with the argument proposed by Aguiar and Gopinath (2007) that the potential output in emerging countries is a variable that is fluctuating through time stochastically and thus has its own cycles as well. Such an interpretation of the double-HP filter is also consistent with the view that the technology shocks at least partially drive the potential output, as argued by Lippi and Reichlin (1994). The double-HP approach applied in this paper yields a potential growth rate that is fluctuating due to random shocks with a volatility of roughly 1.8 percent.around an exponential trend with an average slope of 4.4 percent.

Once we are over with defining the growth cycles in Turkey, we next turn to the second concern that we have, namely, to formulate a view as to the direction that the economy heading in the near future. For this purpose, we propose a new Composite Leading Indicator (CLI) for the Turkish economy. The procedure we follow to construct the CLI is similar to the CLI framework of the OECD. First, we determine the growth cycle turning points in the GDP growth cycle using Bry-Boschan procedure parameterized to better represent the Turkish growth cycle turning points. Next, we choose an ample number of candidate series that can be regarded as being related to the future values of the GDP. The candidate series are inspected for their capacity to herald the future developments in the GDP. The series that have such a capacity are aggregated to form the CLI.

The new CLI that is constructed leads the GDP cycle with three months with a correlation coefficient about 0.9. The CLI leads almost all the growth cycle turning points in the

GDP, and its good performance stays intact in the post-2009 period for which the recent revision in national accounts undertaken by the Turkish Statistical Institute registered a drastic divergence from the old series. Other CLIs had been constructed for the Turkish economy prior to this paper. The most recent one was constructed by Atabek et al. (2005). Nevertheless, this CLI has been performing under par in recent years, clearly calling for an update. Notwithstanding our main methodological contributions, namely, redefining the Turkish growth cycles in a more appropriate way, and modifying the Bry-Boschan procedure to better represent the growth cycle turning points, our CLI also fills the gap by replacing the previous one that has been giving implausible and wrong signals recently. Besides, the aforementioned revision in the national accounts rendered the previously constructed leading indicators virtually useless, especially in the post-2009 period.

The CLI is meant to lead the GDP growth cycle by definition. Hence, an estimate of the next direction that the CLI will take means that we will have a view about the movements in the GDP that will likely take place months in advance than when the data about the period in question is actually available. Arguably, the most important contribution of our paper is the calculation of the CLI turning point probabilities. The seminal contributions about the calculation of business cycle turning point probabilities had taken place during the heyday of business cycle research, the leading paper being Neftci (1982). The sequential probability method promoted by this paper (Neftci method hereafter) has been more or less the industry standard in calculating turning point probabilities. Our method builds on the Neftci method as well, but we have two crucial contributions. The first one is about the business cycle asymmetry. In the terminology of the seminal paper by Sichel (1993), the Turkish GDP and the other main macroeconomics aggregates exhibit both deepness and steepness, like many other countries (see Ozbilgin, 2016, for example). That is, the contractions are more severe compared to expansions, and recovery is slower relative to the pace at which the economy plunges into a recession. To the best of my knowledge, this paper is the first one that takes into account the both aspects of business cycle asymmetry into account in an appropriate way when calculating the turning point probabilities. This task is accomplished by using a flexible distribution into that can handle negative skewness and fat-tails. Our second contribution is about the regime switch probabilities that need to be taken into account in Neftci type methods. Neftci (1982) treats those probabilities as coming from duration dependence, namely the imposed inverse relationship between longevity of the regime and the probability of switching. Diebold and Rudebusch (1989) find that approach implausible and take the regime switch probabilities as constants. In this paper, we propose a method by which the a priori peak and trough probabilities are pinned down from the data. In this way, the a priori probabilities are cycle-dependent, as well as being location-dependent within a cycle. In other words, our method nicely inherits all the nice features of Neftci method, that is, it takes into account the whole process of the development of a cycle into account, but also does more by taking into account the features of the particular cycle that the economy is at, as well as the asymmetry properties of the overall cycle. The new method of calculating the a priori probabilities improves the forecast performance at the growth-cycle peaks. The use of a distribution that can handle negative skewness and fat-tails improves the forecast performance at the troughs. Overall, the method brings significant contributions for calculating the turning point probabilities for the developing and emerging markets for which the deepness and steepness are important features data, and the amplitude varies significantly across cycles.

2 The Growth Cycle

2.1 Frequency Transformation of the GDP Series

For the sake of political practicality, the CLI will be constructed as a monthly statistic. On the other hand, the economic activity that the CLI will be meant to foresee is measured on a quarterly basis, namely, the Gross Domestic Product (GDP). Hence, the first step is to choose an interpolation method to transform the frequency of the GDP from monthly to quarterly. There are various methods to perform such a transformation. Figure 1 exhibits the seasonally adjusted outcome from six of the most commonly used techniques: Linear interpolation, cubic splines, piecewise cubic Hermite interpolating polynomials (PCHIP), Fernandez method, Litterman method, and the Chow-Lin Method[1]. The latter three methods make use of a reference series that is believed to move through time in similar ways like the GDP, but available at the targeted frequency, which in our case, the monthly frequency. A natural candidate that is commonly used in interpolating GDP values is the Industrial Production Index series. As seen in Figure 1, the Fernandez, Chow-Lin, and Litterman methods produce quite similar monthly GDP series. Figure 1 also reveals that the GDP series generated by linear interpolation and PCHIP are very much alike, whereas the other four techniques including the ordinary cubic splines generate a significantly more volatile monthly GDP.

In this study, we opt for linear interpolation like the OECD for three reasons. First and foremost, it is hard to find a reference series to use that can represent the movements in GDP at a monthly frequency. The relationship between the IPI and the GDP is very much distorted in recent years, especially after the revision in the national accounts undertaken by the Turkish Statistical Institute (TSI) in late 2016. In what follows, we will see that interpolation method does not matter much thanks to our method of extracting cycles. However, the interpolation methods differ significantly with respect to their implications about underlying variability in potential output, and this constitutes the second reason as to why we choose to proceed with the linear interpolation. We will return to this topic later.

2.2 Definition of the Growth Cycle

When it comes to defining the cycles, it might be beneficial to start with the semantics. Our primary concern is to acquire a medium-term outlook about the current state of the economy. The policy responses are not meant to be targeted toward short-term movements that are poised to revert within a relatively short period of time. Further, notwithstanding their utmost importance, the movements in trend growth rate are also not the within the

[1] The reference papers for these methods are Fernandez (1981), Chow and Lin (1971), and Litterman (1983).

domain of influence of fiscal and monetary policies, but they are rather to be combatted by structural policies and reforms. We want to filter the GDP series, which supposedly represents the economic activity, in a way to account for these concerns. Further, we will be comparing the current activity against a benchmark, that is the long-term trend in the series, which will be interpreted as the potential output in the economy. We will follow the terminology of the OECD in terms of naming the certain phases throughout the GDP cycle. This terminology is summarized in Figure 2.

Beforehand, the interpolated GDP series is cleansed from seasonal effects using the Tramo-Seats procedure. It is crucial that the calendar effects peculiar to Turkey are taking into account, in particular, the religious and the national holidays. This task is accomplished by feeding the Tramo-Seats procedure with an extra regression variable that is comprised of a monthly record of our holidays.

It is common to use the HP-filter[2] to obtain the cyclical movements in economic series. However, the cycles yielded by HP-filter is not suitable for the purposes of this paper. Figure 3 depicts the cycles obtained by this filter when the two most commonly smoothing parameters used in the literature for monthly data are applied. As seen in the figure, the cycles generated by this filter are too volatile to give a medium-term picture of the economy. There are also too many movements that die shortly after they had started, suggesting a lower persistence than a medium-term perspective would warrant. A policy response towards such movements would be irrelevant because they just revert by themselves in a short period of time.

In this paper, we will use the double-HP approach suggested by the OECD System of Leading Indicators, but with important differences. The double-HP approach is similar to band-pass filters suggested by Baxter and King (1999) and Christiano and Fitzgerald (2003) in the sense that it eliminates movements in the series with high-frequency and the low-frequency, as the former corresponds to irregular components and the latter corresponds to trend. In order to eliminate trends and irregular components, the researcher has to take a stance about the cut-off frequencies. Let's say the frequencies higher than τ_H is thought as pertaining to the noise in data, and the frequencies lower than τ_L as pertaining to the trend. Maravall and del Río (2001) provides a formula for translating the frequency bounds τ_H and τ_L to the defining parameter of the usual HP filter:

$$\lambda_i = \frac{1}{4}\left[1 - \cos\left(\frac{2\pi}{\tau_i}\right)\right]^{-2}, \quad i = H, L.$$

The application of the double-HP filter to the series X is undertaken as follows: First, the series X is detrended by applying the usual HP-filter with the parameter λ_L. This way the frequencies lower than $\tau_L$are eliminated. Let us call the resulting series as $\bar{X}$. Next, we apply the HP-filter with the parameter λ_H to the series $\bar{X}$, but this time we keep the trend component so as to eliminate the frequencies higher than τ_H. The resulting series is called the cyclical component of the series X, and the remainder is called the trend component.

The OECD recommends eliminating frequencies out of 12 to 120 months. However, for Turkish data, these parameters still lead to survival some of the short-lived movements

[2]For HP-filter, see Hodrick and Prescott (1997).

in the normalized cyclical component. So in practice we proceed as follows. We start with $\tau_H = 12$ months like suggested by the OECD, and increase τ_H one by one until no movements that revert in 6 months could survive in the filtered series. At the end, for the Turkish GDP, the parameter τ_H turns out to be 18. For comparison, Figure 3 also presents the cycles computed by the double HP filter with $\tau_H = 12$. Lastly, the cyclical component X^C is normalized as $\hat{X}^C$ using the formula below[3]

$$\hat{X}_i^C = \frac{X_i^C - \frac{\sum_{j=1}^{T} X_j^C}{T}}{\frac{\sum_{h=1}^{T} \left| X_h^C - \frac{\sum_{j=1}^{T} X_j^C}{T} \right|}{T}} + 100,$$

Where T is the sample size.

As seen in Figure 3, the double HP approach leads to a smooth cycle, representing the underlying medium-term trends nicely. As mentioned above, the usual application of the HP filter is hopeless in representing the medium-term picture in the economic activity. In Figure 3, we also present the cycles yielded by the two most commonly applied band-pass filters, Baxter-King (BK), and the Christiano-Fitzgerald (CF). Both the BK and CF filters are also calibrated to eliminate the frequencies outside the range of 18 to 120 months. What is apparent from the figure is that the BK filter still leads to cycles in which some shorter-term movements survive. Also, the data points from the beginning and the end of the sample are lost due to the construction of this filter. In this sense, the BK filter is not suitable for this study. The CF filter on the other hand yields cycles similar to the double-HP filter. The diversion of the two filters is apparent at the beginning and the end of the sample. This is inline with the finding of Nilsson and Gyomai (2011) that the revision sizes up to roughly 2 years are significantly smaller for HP filter than the CF filter. The same study also documents that turning point detection is more stable for the former than the latter. Mainly due to these two reasons, we will conduct the rest of the analysis using the double HP filter.

We will conclude this subsection by revisiting the frequency transformation methods, but this time in terms of the cycles and trends that emerge under each method. As seen in Figure 4, the cycles generated from GDP series obtained under various transformation methods are very similar. The real difference surfaces when we inspect the trends, which have the interpretation as the potential GDP fluctuating stochastically around a deterministic trend. We can observe from the figure that, if the monthly GDP is obtained with methods other than linear interpolation or PCHIP, the fitted shocks governing the process of potential GDP would be significantly higher with much less persistence than we would have obtained under these two methods. Hence the choice of the interpolation method actually means taking a stance about the shocks governing the underlying stochastic process governing the potential GDP. Together with the fact that Fernandez-type methods rely on the weak relationship between the IPI and the GDP, the implications about highly

[3]Alternatively, one could use the logarithms of the series. Nevertheless, some component candidates can possibly assume negative values, which makes taking logarithms infeasible.

volatile shocks to the potential render linear interpolation and PCHIP methods as better alternatives.

2.3 Implications About Shocks to Potential Output Under Alternative Filters

The trend component of the GDP is usually interpreted as the potential GDP by the macroeconomists. For the application of band-pass filters, high-frequency fluctuations may be interpreted as transitory shocks affecting the short-to-medium term growth performance[4], while the deterministic part of the potential growth rate (the average slope of the potential output curves in Figure 5) are determined by deep fundamentals such as the level of human capital stock, the level of science and technology knowledge stock, the stock of institutions, the stock of democratic customs, among others. Figure 5 exhibits the potential GDP implied by the alternative filters. Expectedly, the average growth rates of the potential GDP implied by each filter are close to each other, but still, the average growth rate in the potential GDP ranges between 4.3 percent to 4.5 percent as seen in Table 1. Under the standard applications of the HP filter, the unit-root behaviour of the HP-filter trend, in turn, rules out stochastic trends with significant variation in the growth rates, which have been regarded as important for the emerging economies after the "cycle is the trend" concept introduced by the seminal paper by Aguiar and Gopinath (2007).

We can also observe from Table 1 that fitting a deterministic exponential trend to the potential output yields residuals with a standard deviation of 1.8 and 2.1 percent for the double HP and CF filters, whereas the implied shock volatility for the BK filter significantly higher for the BK filter, at around 3.5 percent.

2.4 A Digression About the Endpoint Problem

The endpoint problem of the two-sided filters is long-recognized (see Kaiser and Maravall (1999), for example). The OECD framework that this paper follows closely ignores the endpoint problem when defining cycles. This section exemplifies the perils of ignoring the endpoint problem and proposes a solution similar to the methods proposed by Kaiser and Maravall (1999) for example[5].

In Figure 6 we can see several examples about the problem and the proposed solution.The method that I use amounts to fitting an AR process with 12 lags to take a 12 months-ahead forecast , then applying the double HP-filter to the resulting series. I will dub this method "the extended forecast method". Let us start with Example 1, and let us assume that we are back in time, in July, 2009. With the benefit of hindsight, we know that June, the previous month, was a trough point. However, if we were back in July 2009, and applied the double-HP filter naively, we would still think that the slowdown was continuing and the cycle was getting deeper. That is, we would fail to detect that a trough

[4]This interpretation is implicit in the position taken by the IMF and the OECD. See Gyomai and Guidetti (2012) and various Country Selected Issues documents by the IMF.

[5]See Gerdrup et al. (2013) for a practical application of a similar method. See Mohr (2005) for a criticism of these methods.

had occured the previous month and the recovery started in the current month. As can be seen from the graph, the extended forecast method remedies the problem and indicates a turning point -albeit one month earlier- which can be verified with the benefit of hindsight. Indeed, if we kept applying the naive double-HP filter with the coming data, we would only be able to detect a turning point when the data for August 2009 arrived.

Figure 6 provides other examples that can be interpreted similarly. The examples indicate that the extended forecast method provides a nice avenue to deal with the endpoint problem when applying the double-HP filter. Clearly, more research regarding this matter is called for.

3 Definition of the Business Cycle Turning Points

The cycle computed by using the double-HP filter is considerably smooth. This makes the identification of the turning points of the cycle remarkably easy. In fact, one can identify the turning points by visual inspection. In any case, to discipline our effort, we follow the OECD in choosing the business cycle (BC) turning points by using the Bry and Boschan (1971) procedure.

The BB procedure automizes the Burns and Mitchell procedure outlined in Burns and Mitchell (1946). As the task of smoothing is undertaken by the double-HP filter, we omit the smoothing part of the original BB procedure and use the modified BB procedure of Harding and Pagan (2002). The first restriction that the BB procedure imposes on data follows from the observation that a peak (trough) is a local maximum (minimum). Hence a data point X is a candidate for being a turning point if it is greater or smaller than the values k periods back and ahead in time. Such a restriction is necessary but not sufficient, as there can be oscillations in the data with a lot of short-lived cycles within which X is still the local maximum or minimum. Hence, the second restriction that the BB procedure imposes is that a phase of a cycle lasts at minimum m periods. In other words, a downward (an upward) movement will take at minimum m months before ending up in a trough (peak). The last restriction specifies the full length of the cycle. A full cycle, that is, a period between a peak and the next peak, or a trough and the next trough is assumed to take at minimum n months. The Bry-Boschan algorithm further imposes certain logical rules, so that the peaks are really peaks and the troughs are really troughs:

1. The peaks and troughs should alternate.

2. The subsequent peaks and the subsequent troughs should be eliminated by choosing the highest and the lowest in the sequence respectively.

3. A trough should be lower than the preceding peak, and vice-versa.

4. There should not be a turning point within the phase length at the beginning and the end of the data.

If the purpose is to follow the Burns and Mitchell, and NBER dating procedure, then one should set $k = 5$, $m = 5$, and $n = 15$. These values for the user-defined parameters, however, are specified for the US economy, and may not be suitable for other countries. For example, such values for k and m lead to too many BC turning points for some variables in Turkey, and possibly other emerging countries, due to the high variability in the data. In this study, we set $k = 6$ and $m = 9$ so that small oscillations such as the small decline in the cyclical component between September 2002 and March 2003 would not be identified as a business cycle turning point (see Figure 7).

In figure 7, we depict the growth cycle turning points of the Turkish economy. The recent crises experienced by the Turkish economy is clearly visible in the figure. In Table 2, the main characteristics of the four economic crises are also displayed. These are the 1993-1994 Banking Crisis, 1997-1998 Russian Crisis, 2001 Currency Crisis, and 2007-2008 Global Financial Crisis. Among the four major crisis, the ramifications of the Global Financial Crisis was apparently the most severe on the Turkish economy, as largest output gap was observed during this period when the economic activity fell almost 4 percent below the potential. The total decline from the previous peak in December 2007 to the trough point in June 2009 was almost 7 percent. It is remarkable that such a huge decay took place in only 18 months. In terms of the pace of recovery, the 2001 Currency Crisis was the worst among recent crises. It took agonizing 34 months for the economy to reach the potential from the trough point. The economy spent a whole 3.5 years under the potential.

What we also observe from Figure 7 is the inability of the economy to push up above potential in the post-2011 period, as the upturns thereafter are interrupted by short-lived downturns. The economic activity seems to be falling drastically beginning from September 2009, and falling under potential as of March 2016. In terms of the distance from potential GDP, the extent of the latest slowdown has passed the trough point of the 2001 Currency Crisis.

4 The construction of the Composite Leading Indicator

The purpose of a composite leading indicator (CLI) is to use certain data that is positively correlated to the future values of the Gross Domestic Product (GDP) to infer information about the future course of the economy. In essence, the CLI can provide valuable information months before the actual GDP data is available, first because it by definition leads the GDP cycle, and second, because it is constructed by using the variables for which the data is available in a more timely manner.

In the construction of the CLI, we follow closely the guidelines in the OECD System of Leading Indicators (see Gyomai and Guidetti (2012)). The first step towards building a CLI is to choose the candidate series which have the potential to herald the future developments in the economic activity beforehand. The selection of the candidate series may follow from the established relationships in the economic theory, or may come from practical knowledge and expertise. An equally important limitation is the data availability and timeliness. A series is useless for the purposes of CLI if its data is coming so late, and at the same time, its leading period is not large. Similarly, series that are subject to serious revisions after a while are also not desirable.

For the Turkish economy, we have chosen 73 such variables which we think to be capable of providing important information about the current and future unobservable state of the economic activity. As mentioned before, the economic activity is approximated by the linearly interpolated monthly GDP series. The candidate series are listed in the data appendix. They include survey variables such as several indicators from the Business Tendency Statistics and Real Sector Confidence Index, a number of monetary and financial variables, a set of balance of payments variables, construction variables, and various variables related to real sector production and aggregate demand, as well as public finance, and employment.

After selecting the candidate series, the next step is the compute the medium-term cycles in each series. This task is accomplished in the same manner the linearly interpolated GDP is treated. That is, the variables are filtered for seasonal effects using the Tramo-Seats procedure as a first step. Once the deseasonalization is undertaken, the growth cycle component of the series are computed using the double-HP filtering procedure, and amplitude-adjusted as explained in the previous section. Lastly, the modified Bry-Boschan algorithm is applied to determine the turning points in the series.

4.1 Choosing the CLI components from the candidate series

Once we obtain the growth cycle components, we check if the candidate series is capable of leading the GDP cycle. In particular, we check the cross-correlation between the series and the GDP to see if the past values of the series are significantly correlated with the GDP. It is also important to check if the leading relationship is valid around BC turning points. For example, the capacity utilization rate is a typical variable that leads the cycle during the normal times, but lags it around peaks and troughs. Further, the candidate series should not give too many false signals. The monetary aggregates and the stock exchange data are typical examples for this issue. For Turkey, for example, the BIST transaction volume cycle leads almost every turning point in the GDP cycle. Nevertheless, it has way too many peaks and troughs that it cannot be relied on comfortably to assess the future direction of the economy.

We inspect the 73 series along these lines and end up choosing 10 of them that hold information about the current and future values of the GDP. The cycles observed in these variables, and their cross-correlation with GDP are depicted in Figure 8. The leading performance of some of the series, like the Passenger Car Sales, is very clear. While for some variables, like the Energy Imports, the leading performance is inferior compared the past in the post-2009 period for which the TSI revision of late 2016 affected the GDP figures drastically. Hence, the variables as such should be monitored carefully in the upcoming months to reassess their leading performance. For the post-2009 period, the performance of the Banking Sector Net Foreign Liabilities in leading the GDP peaks and troughs is remarkable. Actually, banks' foreign borrowing is one of the few variables among the large set of variables that we have investigated, together with Agricultural Exports and Energy Imports, that can match the amplitude of the recently plummetting economic activity. The cycles of the new GDP series that emerged after the TSI revision seems to be driven to a great extent by the cycles in the foreign borrowing through the banking sector, as seen in Panel 8 of Figure 8. Our analysis reveals this channel that appeared with the new GDP series. Definitely, further research is needed to work out the mechanisms through which this channel operates.

4.2 The CLI and its performance

After the component series are chosen, we follow the OECD as a first step and take a simple average of the normalized cyclical values of the components to get the CLI. The resulting CLI is depicted in Figure 9. The shaded areas represent the periods of downturn and slowdown consistent with the dates in Figure 7. The cross-correlation function is presented in Figure 10. The maximum correlation occurs at the third lag of CLI, with a coefficient of 0.89. As mentioned above, the TSI revision of December 2016 affected the post-2009 period GDP drastically. Thus we paid special attention to pick the variables whose post-2009 performance is satisfactory, and could only find a few. Still, the post-2009 correlation of the CLI is still very high, with a maximum of roughly 0.85, again at the third lag.

As can be observed from Figure 9, the CLI foresees almost all the recent turning points in the new GDP series. The leading performance of the CLI around GDP turning points is summarized in Table 3. The CLI is able to signal 11 out of 13 turning points in the GDP since 1993. The troughs in October 2001 and July 2012 also correspond to trough points in the CLI. In other words, the CLI produced coincidental signals at these points. Nevertheless, the CLI data arrives 3 months earlier than the actual GDP. Hence, for these two troughs that CLI failed to foresee, the CLI still provides an early warning. Finally, the CLI generated only two false signals in the whole sample period.

One apparent problem with the new CLI is its inability to match the amplitude of the growth cycles after 2011. As seen in Figure 9, the cycles are too shallow for this period. This makes the calculation of the turning point probabilities difficult. We next turn to this issue.

5 Turning Point Probabilities

A turning point is when the economy gets out of a downturn or slowdown period, or when the economy comes to the end of an expansion or a recovery period. It is thus of utmost importance from a policy-oriented perspective to have a stance as to whether a turning point is approaching or not. Given that the CLI by definition leads the GDP cycle, a turning point probability relying on the latest information inferred from the CLI gives a view about the direction that the economic activity will likely follow months in advance.

5.1 Asymmetry in Turkish Growth Cycles

Our first effort towards calculating turning point probabilities relates to recognizing the statistically significant asymmetry in the Turkish production data. Sichel (1993) is the seminal paper on first using the terms *Steepness* and *Deepness* for conceptualizing cyclical asymmetries. In Sichel's definition, a cycle is deep if peaks are shorter than troughs are deep. A cycle is steep if upswing phases (recovery plus expansion) take longer than downswing phases (downturn plus slowdown). Figure 11 depicts a generic deep and steep cycle. A visual inspection of the cyclical Turkish GDP and the Industrial Production (IP) data reveals that the Turkish data exhibits both deepness and steepness. This observation can be verified by more rigorous analysis[6]. Tanriover and Yamak (2015) provide evidence towards deepness and steepness in Turkish GDP cycle using Newey and West (1987) procedure. Using other tests proposed in the literature indicates further evidence along this line[7].

We also start with to test for asymmetry using the Newey-West procedure as proposed by Sichel. Sichel's first observation is that a series exhibits negative skewness if it has deepness. Similarly, the difference of a series exhibit negative skewness if the series has steepness. The skewness in the growth cycle, y, is given as below:

$$S_y = \frac{\sum_{t=1}^{T} (y_t - \bar{y})^3}{T (\sigma_y)^3}.$$

Next Sichel uses the procedure suggested by Newey and West (1987) to test for the significance of skewness. The idea is to construct a variable y_t as below

$$y_t = \frac{(y_t - \bar{y})^3}{\sigma_y}.$$

Then, the regression of y_t on a constant gives an estimate of S_y. In turn, the significance of the constant would indicate the significance of sample skewness.

The test of steepness would follow the same lines. Only that, the first difference of the growth cycle is used instead of the growth cycle in levels. The results indicate that the Turkish growth cycle exhibits deepness at 1.3 percent significance level. The skewness in differences is significant at 0.004 percent significance level. Hence, the Newey-West method suggests pretty strong evidence towards business cycle asymmetry in terms of both deepness and steepness.

Next we will use the deepness yardstick proposed by Hansen and Prescott (2005). They use the verbal definition of deepness, that is, the peaks are shorter than troughs are deep for a series that exhibit deepness. In line with this definition, a ratio D can be calculated from data on growth cycle, y:

$$D = \frac{mean\,(y > 0)}{|mean\,(y < 0)|}.$$

If $D < 1$, the series exhibit deepness, because then the average negative deviations from trend are bigger in amplitude than the positive deviations from trend. We have that $D = 0.83$, which indicates that Turkish growth cycle is quite deep. For comparison, the deepness in the US GDP cycle is historically around 0.93[8].

[6]Ozbilgin (2016) documented deepness in the Turkish business cycles with a group of other developing and developed countries.

[7]See also Atabek et al. (2005).

[8]See Özbilgin for further international evidence on deepness in GDP.

Our next test follows from the fact that, under the null hypothesis of normality, both the sample skewness and kurtosis are distributed normally. The definition of skewness is given above. The excess kurtosis is given by[9]

$$K_y = \frac{\sum_{t=0}^{T} (y_t - \bar{y})^4}{\sum_{t=0}^{T} (y_t - \bar{y})^2} T - 3.$$

Joanes and Gill (1998) suggest that the calculation of the skewness and kurtosis in small samples requires a correction, so that the adjusted skewness, $\tilde{S}_y$, and the adjusted kurtosis, $\tilde{K}_y$, are given by the expression below:

$$\begin{aligned} \tilde{S}_y &= \frac{S_y \sqrt{T(T-1)}}{T-2}, \\ \tilde{K}_y &= \frac{(T-1)[K_y(T+1)+6]}{(T-2)(T-3)}. \end{aligned}$$

Cramer (1998) provides the following expression for the standard error of skewness and that of kurtosis:

$$\begin{aligned} SE(S_y) &= \sqrt{\frac{6T(T-1)}{(T-2)(T+1)(T+3)}}, \\ SE(K_y) &= 2SE(S_y)\sqrt{\frac{T^2-1}{(T-3)(T+5)}}. \end{aligned}$$

The expression below is then a statistics to test if the sample skewness is significantly different than 0:

$$y^s = \frac{S_y}{SE(S_y)}.$$

Similarly, below is a statistics to test if the sample kurtosis is significantly different than 0:

$$y^k = \frac{K_{y^c}}{SE\left(\tilde{K}_{y^c}\right)}.$$

[9] Joanes and Gill (1998) suggest that the calculation of the skewness and kurtosis in small samples requires a correction, so that the adjusted skewness, $\tilde{S}_{y^c}$, and the adjusted kurtosis, $\tilde{K}_{y^c}$, are given by the expression below:

$$\begin{aligned} \tilde{S}_{y^c} &= \frac{S_{y^c} \sqrt{T(T-1)}}{T-2}, \\ \tilde{K}_{y^c} &= \frac{(T-1)[K_{y^c}(T+1)+6]}{(T-2)(T-3)}. \end{aligned}$$

In our applications, these corrections do not make a difference.

For our sample, we have $y^s = -4.30$. This statistic suggests that the null hypothesis that the skewness is zero is rejected at 0.002 percent significance level. As to the kurtosis, we have $y^k = 1.86$, suggesting that the kurtosis is different than 3 at 6.3 percent significance level.

The statistics about the skewness and kurtosis above suggest that the distribution of the Turkish growth cycle is unlikely to be normal. We can also check whether this argument is supported by standard tests of normality. The application of four popular tests for normality, Jarque-Bera, Kolmogorov-Smirnov, D'Agostino-Pearson, and Shapiro-Wilk tests all reject the null hypothesis of normality at 0.01 level of significance for both the level and the first difference of the cyclical component.

The cyclical GDP and the difference of the cyclical GDP exhibit skewness which cannot be statistically rejected, indicating that the series are both deep and steep. Similarly, the normality of the cyclical component is rejected for both the level and the difference of the cyclical series. Given these findings, we want our method to capture the relevant asymmetry in the data in order not to overestimate the turning point probability towards a recovery and underestimate the turning point probability towards a downturn. Also again due to strong steepness and deepness, we do want our probabilities to be cycle-specific.

5.2 Calculation of the turning point probabilities

The sequential probability method proposed by Neftci (1982) provides an excellent framework where we can incorporate our concerns. The Neftci method yields a decision rule to recursively calculate whether the latest observation in a series is a turning point using Bayesian techniques. In particular, the method utilizes the past pattern of the series together with the last period's posterior probability. In this respect, the Neftci method is a pioneer in differentiating the signal strength of the latest data. The decision rule to calculate the turning point probability from a downswing to an upswing under Neftci method is given below.

$$P_t = \frac{\left[P_{t-1} + \Gamma_t^{\tau}\left(1 - P_{t-1}\right)\right] f_t^u}{\left[P_{t-1} + \Gamma_t^{\tau}\left(1 - P_{t-1}\right)\right] f_t^u + \left(1 - P_{t-1}\right) f_t^d \left(1 - \Gamma_t^{\tau}\right)} \tag{1}$$

Above, P_t is the posterior trough probability at time t. The variables f_t^d and f_t^u refer to the conditional densities of the latest data point is if it is coming from downswing and upswing regimes[10] respectively.

The symbol Γ_t^{τ} stands for the probability of a trough provided that a trough has not already occurred. For calculating a turning point from an upswing to a downswing regime, one has to replace f_t^u and f_t^d and use Γ_t^p, that is the probability of a peak provided that a peak has not already occurred.

In what follows, we use the formula (1) to calculate turning point probabilities sequentially, using the latest observation on the CLI, z_T and the last period's probability P_{t-1}. However, we diverge in two dimensions from Neftci (1982), and the similar literature such

[10] The economy is in a downswing regime if it is in the downturn or slowdown phases of the growth cycle. Similarly, an upswing regime is associated with the recovery and expansion phases of the growth cycle.

as Diebold and Rudebusch (1989), Neftci and Ozmucur (1991), and Niemira (1991). The first divergence relates to the significant asymmetry in the Turkish growth cycle documented comprehensively in the previous section. The discussion above establishes that not only is there no evidence towards normality of the cycle, but also the cycle exhibits significant negative skewness and excess kurtosis. A variant of the normal distribution that can deal with skewness is the Skew-Normal (SN) distribution introduced by Azzalini (1985). The SN distribution has an extra parameter, α, that regulates skewness, in addition to the ordinary location and shape parameters, ξ, and Ω[11]. If random variable $z\tilde{} SN(\xi, \Omega, \alpha)$, then $z\tilde{} N(\xi, \Omega)$ when $\alpha = 0$. Reflecting the skewness, $z^2\tilde{}\chi^2_1$.

The SN distribution can handle negative skewness in the data nicely. However, in light of the results of the previous section, the excess kurtosis stands out as an additional characteristic of the data that may be important. A non-Gaussian distribution that can handle heavy tails and negative skewness simultaneously in a flexible way is the Skew-T (ST) distribution introduced by Adelchi Azzalini (2003)[12]. It has four parameters, location, ξ, scale, Ω, shape α, and degrees of freedom, v. The ST distribution is built in similar ways like the Student's T distribution, but instead of the normal distribution, a skew-normal distribution is used by dividing it by the χ^2_v distribution. Say a random variable z is distributed ST, i.e., $z\tilde{} ST(\xi, \Omega, \alpha, v)$. Then if we have $\alpha = 0$, $z\tilde{} t(\xi, \Omega, v)$. When the degrees of freedom parameter goes to infinity, that is, $v \to \infty$, then $z\tilde{} SN(\xi, \Omega, \alpha)$. If we have $\alpha = 0$ and $v \to \infty$ together, then $z\tilde{} N(\xi, \Omega)$.

Like Neftci (1982) and Diebold and Rudebusch (1989), we first divide the observations on the CLI $(z_1, ..., z_T)$ as those belonging to the upswing (z^u) and downswing (z^d) regimes. Then we fit a normal, a skew-normal, and a skew-t distribution to z^u and z^d by the maximum likelihood. While the prevalent application of the maximum likelihood method involves the normal distribution, the use of the skew-normal and the skew-t distribution does not involve any complicacy. Namely, the following problems are solved given the likelihood functions, L^{SN}, and L^{ST},and the densities, f^{SN} and f^{ST}, respectively for the skew-normal and the skew-t distributions:

$$\begin{aligned}
\underset{\xi,\Omega,\alpha}{Max}\ \log L^{j,SN} &= \sum_{t=1}^{T} \log f^{SN}\left(z_t^j; \xi, \Omega, \alpha\right), \quad j = u, d. \\
\underset{\xi,\Omega,\alpha,v}{Max}\ \log L^{j,ST} &= \sum_{t=1}^{T} \log f^{ST}\left(z_t^j; \xi, \Omega, \alpha, v\right), \quad j = u, d.
\end{aligned}$$

While fully capturing the third and fourth-moment properties is not possible in short samples, taking into account these moments may improve our results as still the likelihood of getting the observed skewness is significantly higher when using Skew-t distribution compared to the normal distribution.

Our second divergence from Neftci (1982) and the ensuing literature relates to the calculation of the probabilities $\Gamma^{\tau,p}$ in formula (1). In Neftci's paper, these probabilities

[11] See also Azzalini and Valle (1996) and Azzalini and Capitanio (1999) for detailed information about the Skew-N distribution.

[12] Since their introduction, the Skew-N and Skew-T distributions have been applied in various fields of Science. Their first usage in economics is due to Ozbilgin (2016).

are pinned down from assumptions relating to duration dependence, that is, the regimes end when they become older, in the spirit of a hazard rate. Diebold and Rudebusch take these probabilities as certain constants, in particular set $\Gamma^{\tau} = 0.10$ and $\Gamma^{p} = 0.2$. We use data as well to calculate probabilities $\Gamma^{\tau,p}$. To do so, we fit an AR(1) process to the cyclical component of the series, z_t by the maximum likelihood

$$z_{t+1} = \rho z_t + \varepsilon_t \ , \ \ \varepsilon_t \overset{iid}{\sim} D.$$

The cyclical component is highly persistent and the resulting residuals also exhibit significant negative skewness and excess kurtosis. Hence the distribution D will also be SN, and ST in addition to N. The use of the maximum likelihood to estimate an AR(1) process when the residuals are normally distributed is explained elsewhere in the literature. A concise and clear treatment of the matter can be found in Hamilton (1994). Nonetheless, the application of the maximum likelihood method for estimating AR(1) with SN and ST distributed shocks is a little tricky and not as straightforward as estimating f^{SN} and f^{ST}. We next explain the maximum likelihood estimation of the AR(1) process with the ST distributed shocks. The maximum likelihood estimation with the SN distribution is similar.

We start out with the observation that z_t is distributed skew-t for a certain set of parameters if the residuals ε_t are distributed skew-t. Let $\Theta = \{\xi, \Omega, \alpha, v\}$ be the set of parameters of the distribution and $\varepsilon_t \tilde{} ST(\Theta)$[13]. Unfortunately, the mapping between the parameters of z_t and the parameters of ε_t is not trivial as in the Gaussian case[14]. However, we can use the fact that the moments are functions of parameters in skew-t distribution, $m = h(\Theta)$, where h is a highly nonlinear function. Similarly, through the AR(1) relation, the moments of z_t are functions of those of ε_t, $m^z = g(m^e)$. Hence we can build the likelihood function as follows.

1. For a vector of parameters, $[\Theta_0 \ \rho_0]$, calculate the moments of ε, m_0^{ε}, implied by Θ_0, where $m_0^{\varepsilon} = h(\Theta_0)$.

2. Calculate the moments of z, m^z, implied by m_0^{ε}, and ρ_0, where $m_0^z = g(m_0^{\varepsilon}, \rho_0)$.

3. Calculate the parameters of the distribution of z_t, $\tilde{\Theta}_0$, using $\tilde{\Theta}_0 = h^{-1}(m_0^z)$.

4. The density of the first observation is $f_{z_1}^{ST}\left(z_1; \tilde{\Theta}_0\right)$[15]. The density of the tth observation conditional on the previous observations is simply

$$f_{z_t|z_{t-1}}^{ST}\left(z_t|z_{t-1}; \tilde{\Theta}_0\right) = f_{z_t}^{ST}\left(z_t; \hat{\Theta}_0\right),$$

   Where $\hat{\Theta}_0 = \Theta_0 + [\rho z_{t-1} \ 0 \ 0 \ 0]$. Next we can use the following fact to build the likelihood function in the ordinary way

$$f_{z_t,z_{t-1},\ldots,z_1}^{ST}\left(z_t, z_{t-1}, \ldots, z_1; \hat{\Theta}_0\right) = f_{z_t|z_{t-1}}^{ST}\left(z_t|z_{t-1}; \hat{\Theta}_0\right) \cdot f_{z_{t-1},z_{t-2},\ldots,z_1}^{ST}\left(z_{t-1}, z_{t-2}, \ldots, z_1; \hat{\Theta}_0\right).$$

[13] In the Gaussian case, if $\varepsilon_t \tilde{} N(0, \sigma^2)$, $X_t \ \tilde{} N\left(0, \frac{\sigma^2}{1-\rho^2}\right)$.

[14] Under the normal distribution, $X \tilde{} N\left(0, \frac{\sigma^2}{1-\rho^2}\right)$ if $\varepsilon \tilde{} N(0, \sigma^2)$.

[15] See Azzalini and Capitanio (2003) for the distribution function and the moments of the skew-t distribution. I do not include explicit forms here to save space.

Hence the log-likelihood function is

$$\mathcal{L}(\Theta_0, \rho_0) = \log f_{z_1}^{ST}(z_1; \Theta_0) + \sum_{t=2}^{T} \log f_{z_t}^{ST}\left(z_t; \hat{\Theta}_0\right).$$

From the steps above, $\hat{\Theta}_0$ is a function of Θ_0 and ρ_0. We can then minimize $\mathcal{L}(\cdot)$ with respect to Θ and ρ over the parameter space using ordinary numerical optimization techniques.

Note that, the remarkable nonlinearity of the function $h(\cdot)$ may render the implementation of the above strategy rather hard. An alternative strategy is to estimate the AR(1) process conditional on the initial value, z_1. In this case, one may first get an estimate of the persistence parameter, ρ, using linear regression

$$\hat{\rho} = \left(\tilde{z}'\tilde{z}\right)^{-1} \tilde{z}'z.$$

Where $\tilde{z} = Lz$, that is the first lag of the cyclical component. Then the residuals can be calculated from the fitted values

$$\hat{\varepsilon}_t = z_t - \hat{\rho} z_{t-1}.$$

Then the skew-t distribution, f^{ε}, can be fitted directly to the fitted residuals by the maximum likelihood. For the current paper, and in many other applications, the two methods would lead to very similar results unless the sample size is very small. This is expected as the contribution of the first observation to the overall likelihood is not much for large enough samples. Besides, the conditional maximum likelihood estimator and the exact maximum likelihood distribution have the same large sample distribution for $|\rho| < 1$ (See Hamilton, 1994).

Once the parameters of the AR(1) process are pinned down, we can use the process to calculate the time-dependent a priori trough and peak probabilities in light of Figure 12. Let us first assume that we are in a downswing regime, and we are looking for the probability of a trough at the latest data point. If the latest observation on the CLI is a trough, than the next observation, z_{T+1}, will be higher than the latest observation, z_T. So in other words, we are looking for the probability that z_{T+1} is greater that z_T. Let us define $\Delta z^e = \{z_{t+1} - z_t | z_{t+1} \in Z^u, z_t \in Z^d\}$ where Z^u and Z^d is the set of observations in the upswing and the downswing regimes respectively. Let us denote the mean and the standard deviation of the change in the series when a downswing regime ends and an upswing regime starts by $\mu_{\Delta z^u}$ and $\sigma_{\Delta z^u}$. Then the a priori trough probability can be calculated as below

$$\Gamma^{\tau} = \Pr[z_T + \mu_{\Delta z^e} - \zeta^{\tau}\sigma_{\Delta z^e} < z_{T+1} < z_T + \mu_{\Delta z^e} + \zeta^{\tau}\sigma_{\Delta z^e}].$$

Above, ζ^{τ} is a parameter that can be gauged to improve the fit of the probabilities with respect to in-sample and out-of-sample analyses. The a priori peak probability can be calculated in the same way.

Figures 13 and 14 depict the turning point probabilities that come out of our calculations. The calculations capture the past turning points and have the desired characteristics to be cycle-specific and regime-specific. In other words, the turning point probability for a certain point in the growth cycle is different than that on another point that is located in another cycle but implying the same output gap.

Figure 13 shows the impact of choosing fixed Γ^{τ} and Γ^{p} naively to values used in past literature. The figure reports the results under the values implied by the logic of Neftci and Ozmucur (1991)[16] ($\Gamma^{\tau} = \Gamma^{p} = 0.05$), and the values used by Diebold and Rudebusch (1989) ($\Gamma^{\tau} = 0.10$, $\Gamma^{p} = 0.02$). As seen in the figure, the method used in this paper for calculating the a priori probabilities improves the resulting turning point probabilities significantly, especially at growth cycle peaks. To give an example, the a priori probabilities in the spirit of Neftci and Ozmucur (1991) yield a probability of 0.69 for the peak in August 2000. The application of the Diebold and Rudebusch (1989) probabilities yields a probability of 0.40. The method of this paper, on the other hand, leads to a probability of 0.90 for the same peak. Similarly, the fixed weights in this example fail to capture the recent shallow movements in the CLI and the reference series itself that hamper the calculation of turning point probabilities greatly. As an example, for the August 2013 peak, the method of this paper yields a probability of 0.71. The fixed values of Γ in the spirit of Neftci-Ozmucur and Diebold-Rudebusch produce probabilities of 0.46 and 0.21 respectively.

Next, we inspect the impact of using the skew–t and skew-normal distribution compared to the normal distribution. Using the skew-normal distribution enables us to take into account the observed deepness through densities f^{u} and f^{d}, and the steepness through f^{ε}. The skew-t distribution, on the other hand, facilitates dealing with the fat tails on the top of negative skewness. Figure 14 depicts the performance of the three distributions in calculating the turning point probabilities. As seen in the figure, the use of skew-t and skew-normal distributions bring significant benefits when calculating trough probabilities, especially the relatively shallow ones that are harder to predict. For example, for the trough in September 2014, the skew-t distribution leads to a probability of 0.82, whereas the normal distribution leads to a probability of 0.54.

6 Concluding remarks

This paper aims to contribute to the policymaking toolbox by first, specifying a metric that provides the picture of the current and policy-relevant state of the economic activity, and second, by laying out a framework to analyze the direction that the economy would likely head in the near future.

In this respect, the paper first specifies the growth cycles of the Turkish economy. An exhaustive list of frequency distribution methods and the cycle extraction methods are inspected. We ended up using linearly interpolated GDP series and the double-HP filter as suggested by the OECD System of Composite Leading Indicators. When necessary, our methods involved divergence from the OECD methods, as discussed in the text.

Next, we build a composite leading indicator that is highly correlated with the future values of the GDP. The CLI leads 11 out of 13 growth cycle turning points in the GDP. It is coincidental with the other two. As the CLI data come out in a more timely manner, still an early warning is provided by the CLI for these two turning points. One problem

[16] This boils down to dividing the total number of cycles to the number of observations.

with the CLI is that its recent cycles are rather shallow. This makes it hard to get strong signals about GDP turning points. Nevertheless, the relationship between the recently revised GDP and various component candidates is broken severely especially after the year 2009, making it very difficult to forecast the GDP for this period.

The last part of the paper offers a methodology that builds on Neftci-type sequential probability methods to calculate the growth cycle turning point probabilities. The method brings two contributions to the calculation of turning point probabilities. First, the negative skewness and fat tails that are statistically significant characteristics of the data are taken into account. Second, the a priori probability of a regime change is calculated in a new way from the data. The first improvement brings significant benefits at growth cycle peaks, while the second at the growth cycle troughs.

References

Adelchi Azzalini, A. C. (2003). Distributions generated by perturbation of symmetry with emphasis on a multivariate skew t-distribution. *Journal of the Royal Statistical Society. Series B (Statistical Methodology) 65*(2), 367–389.

Aguiar, M. and G. Gopinath (2007, February). Emerging market business cycles: The cycle is the trend. *Journal of Political Economy 115*(1), 69–102.

Atabek, A., E. E. Cosar, and S. Sahinöz (2005, January). A New Composite Leading Indicator for Turkish Economic Activity. *Emerging Markets Finance and Trade 41*(1), 45–64.

Azzalini, A. (1985). A class of distributions which includes the normal ones. *Scandinavian Journal of Statistics 12*, 171–178.

Azzalini, A. and A. Capitanio (1999). Statistical applications of the multivariate skew normal distribution. *Journal of the Royal Statistical Society: Series B (Statistical Methodology) 61*(3), 579–602.

Azzalini, A. and A. D. Valle (1996). The multivariate skew-normal distribution. *Biometrika 83*(4), 715.

Baxter, M. and R. G. King (1999, November). Measuring Business Cycles: Approximate Band-Pass Filters For Economic Time Series. *The Review of Economics and Statistics 81*(4), 575–593.

Bry, G. and C. Boschan (1971, September). *Cyclical Analysis of Time Series: Selected Procedures and Computer Programs.* National Bureau of Economic Research.

Burns, A. F. and W. C. Mitchell (1946). *Measuring Business Cycles.* National Bureau of Economic Research, Inc.

Chow, G. and A.-l. Lin (1971). Best linear unbiased interpolation, distribution, and extrapolation of time series by related series. *The Review of Economics and Statistics 53*(4), 372–75.

Christiano, L. J. and T. J. Fitzgerald (2003, 05). The Band Pass Filter. *International Economic Review 44*(2), 435–465.

Cramer, D. (1998). *Fundamental Statistics for Social Research: Step-by-Step Calculations and Computer Techniques Using SPSS for Windows.* New York, NY, 10001: Routledge.

Diebold, F. X. and G. D. Rudebusch (1989, July). Scoring the Leading Indicators. *The Journal of Business 62*(3), 369–91.

Fernandez, R. B. (1981, August). A Methodological Note on the Estimation of Time Series. *The Review of Economics and Statistics 63*(3), 471–476.

Gerdrup, K., A. B. Kvinlog, and E. Schaanning (2013). Key indicators for a countercyclical capital buffer in Norway - Trends and uncertainty. *Norges Bank Staff Memo* (13).

Gyomai, G. and E. Guidetti (2012). OECD System of Composite Leading Indicators. Technical report, OECD Publishing.

Hamilton, J. D. (1994). *Time series analysis*. Princeton University Press.

Hansen, G. D. and E. C. Prescott (2005, October). Capacity constraints, asymmetries, and the business cycle. *Review of Economic Dynamics 8*(4), 850–865.

Harding, D. and A. Pagan (2002, March). Dissecting the cycle: a methodological investigation. *Journal of Monetary Economics 49*(2), 365–381.

Hodrick, R. J. and E. C. Prescott (1997, February). Postwar U.S. Business Cycles: An Empirical Investigation. *Journal of Money, Credit and Banking 29*(1), 1–16.

Joanes, D. N. and C. A. Gill (1998). Comparing measures of sample skewness and kurtosis. *Journal of the Royal Statistical Society: Series D (The Statistician) 47*(1), 183–189.

Kaiser, R. and A. Maravall (1999). Estimation of the business cycle: A modified Hodrick-Prescott filter. *Spanish Economic Review 1*(2), 175–206.

Lippi, M. and L. Reichlin (1994). Diffusion of technical change and the decomposition of output into trend and cycle. *Review of Economic Studies 61*(1), 19–30.

Litterman, R. B. (1983). A random walk, Markov model for the distribution of time series. Staff Report 84, Federal Reserve Bank of Minneapolis.

Maravall, A. and A. del Río (2001). Time Aggregation and the Hodrick-Prescott Filter. Working Papers 0108, Banco de España;Working Papers Homepage.

Mohr, M. (2005, July). Trend-cycle (-season) filter. Working paper no.499, European Central Bank.

Neftci, S. N. (1982). Optimal prediction of cyclical downturns. *Journal of Economic Dynamics and Control 4*, 225–241.

Neftci, S. N. and S. Ozmucur (1991). Türkiye ekonomisi için tÜsÝad Öncü göstergeler endeksi. *TUSIAD*.

Newey, W. and K. West (1987). A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica 55*(3), 703–08.

Niemira, M. P. (1991). *An international application of Neftci's probability approach for signalling growth recessions and recoveries using turning point indicators*, Chapter 5, pp. 91–106. Leading economic indicators : new approaches and forecasting records. Cambridge University Press.

Nilsson, R. and G. Gyomai (2011, May). Cycle Extraction: A Comparison of the Phase-Average Trend Method, the Hodrick-Prescott and Christiano-Fitzgerald Filters. OECD Statistics Working Papers 2011/4, OECD Publishing.

Ozbilgin, H. M. (2016). Explaining the deepness. Unpublished manuscript.

Sichel, D. E. (1993, April). Business Cycle Asymmetry: A Deeper Look. *Economic Inquiry 31*(2), 224–36.

Tanriover, B. and R. Yamak (2015, December). Business Cycle Asymmetry: Deepness and Steepness in Turkey. *Romanian Economic Journal 18*(58), 81–96.

Figures

Figure 1. GDP Frequency Transformation, Comparison of Interpolation Techniques

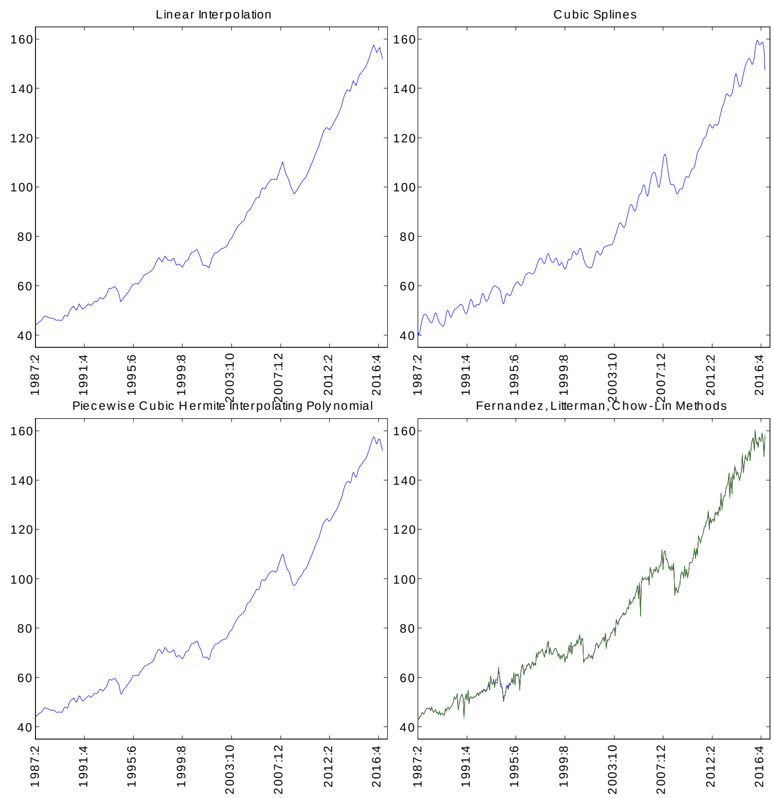


Figure 2. Phases of a growth cycle

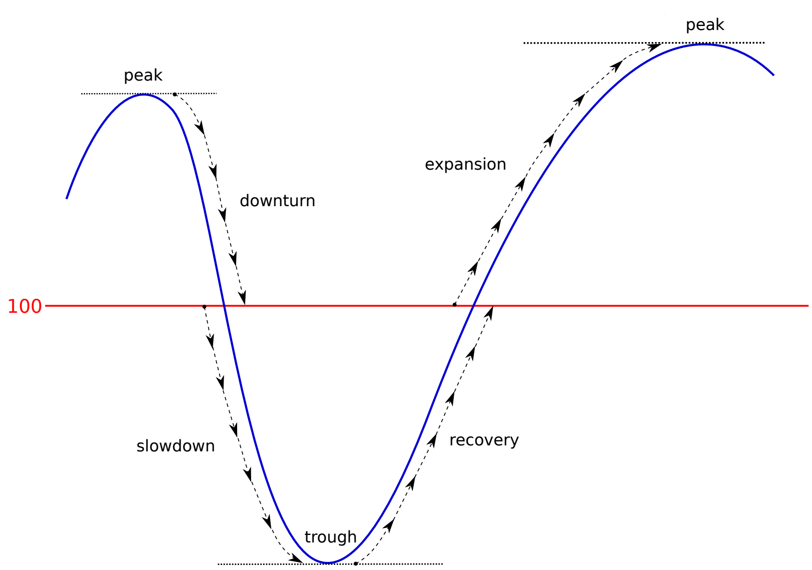


Figure 3. Turkish GDP Cycle Under Alternative Filters

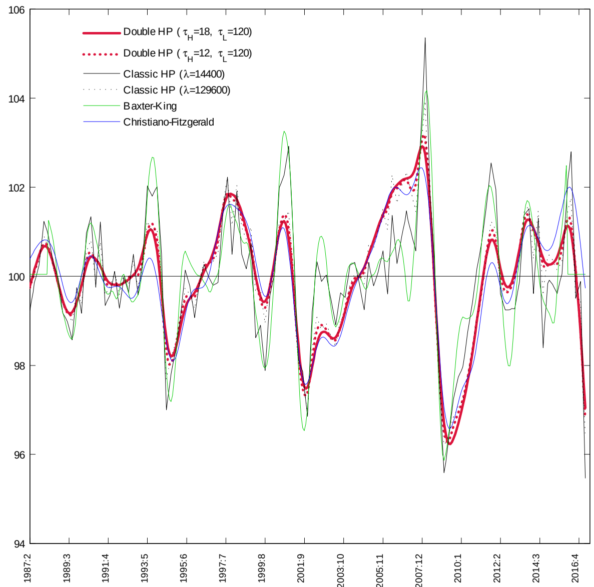


Figure 4. GDP Cycle and Trend Under Various Interpolation Techniques

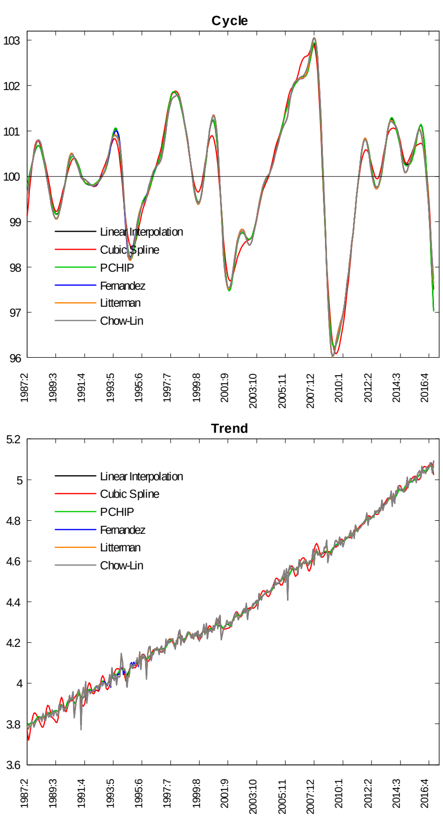


Figure 5. Potential Output Under Alternative Filters

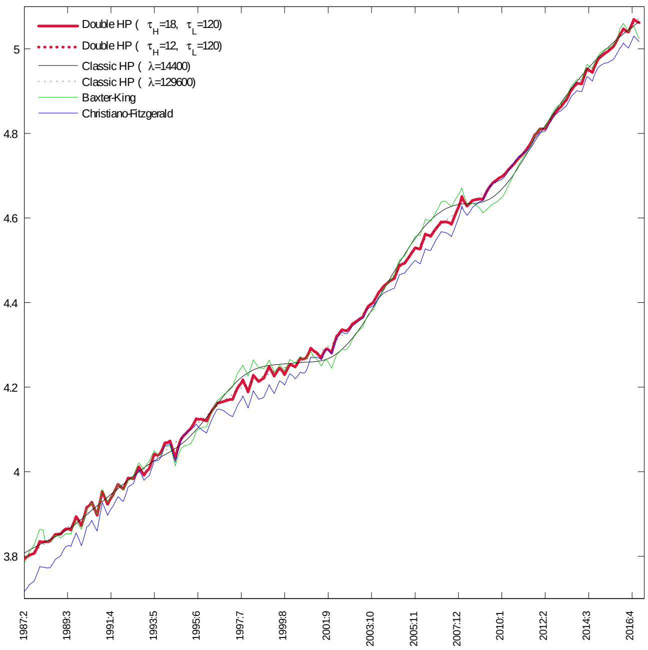


Figure 6. Coping with the End-Point Problem

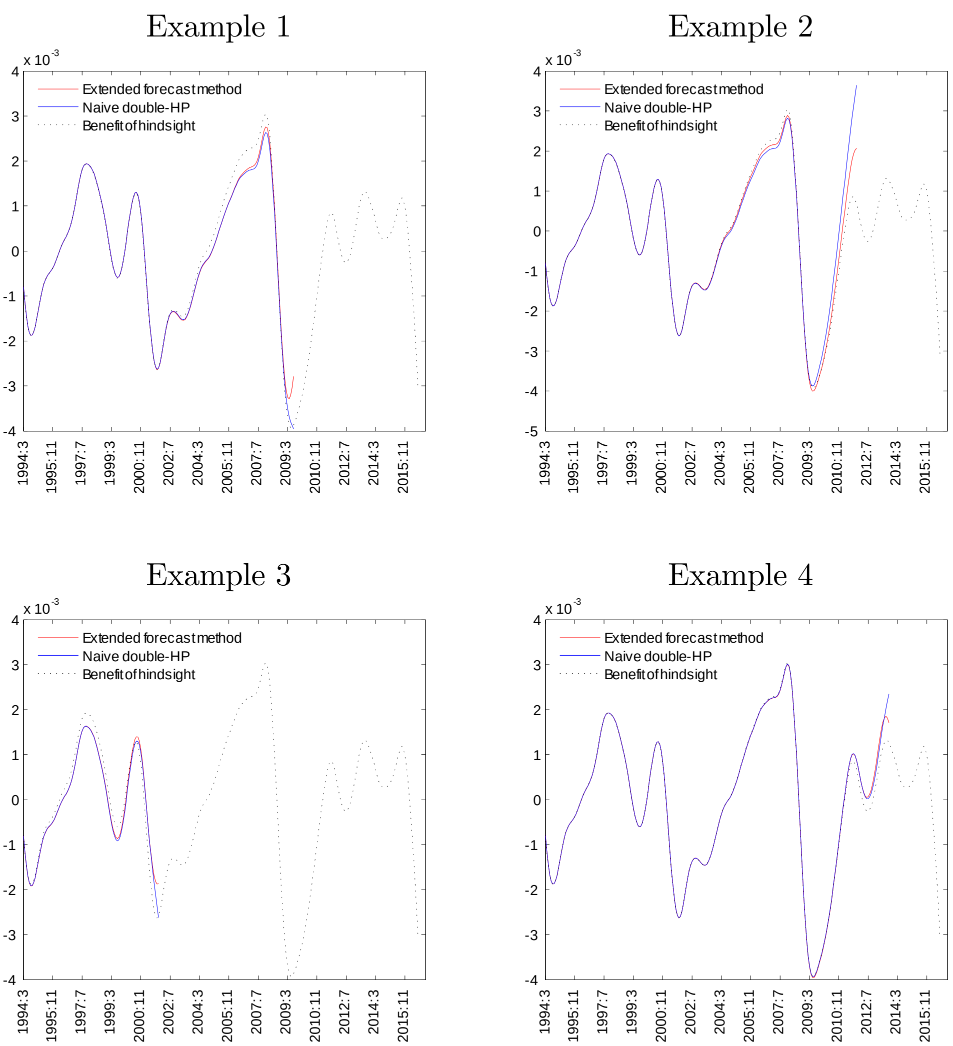


Figure 7. Peaks and Troughs of the Turkish GDP Cycle

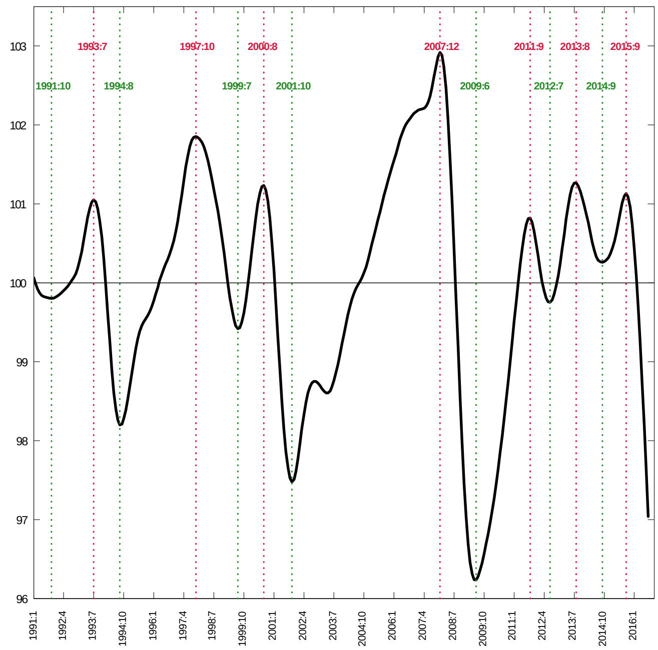


Figure 8. CLI Components

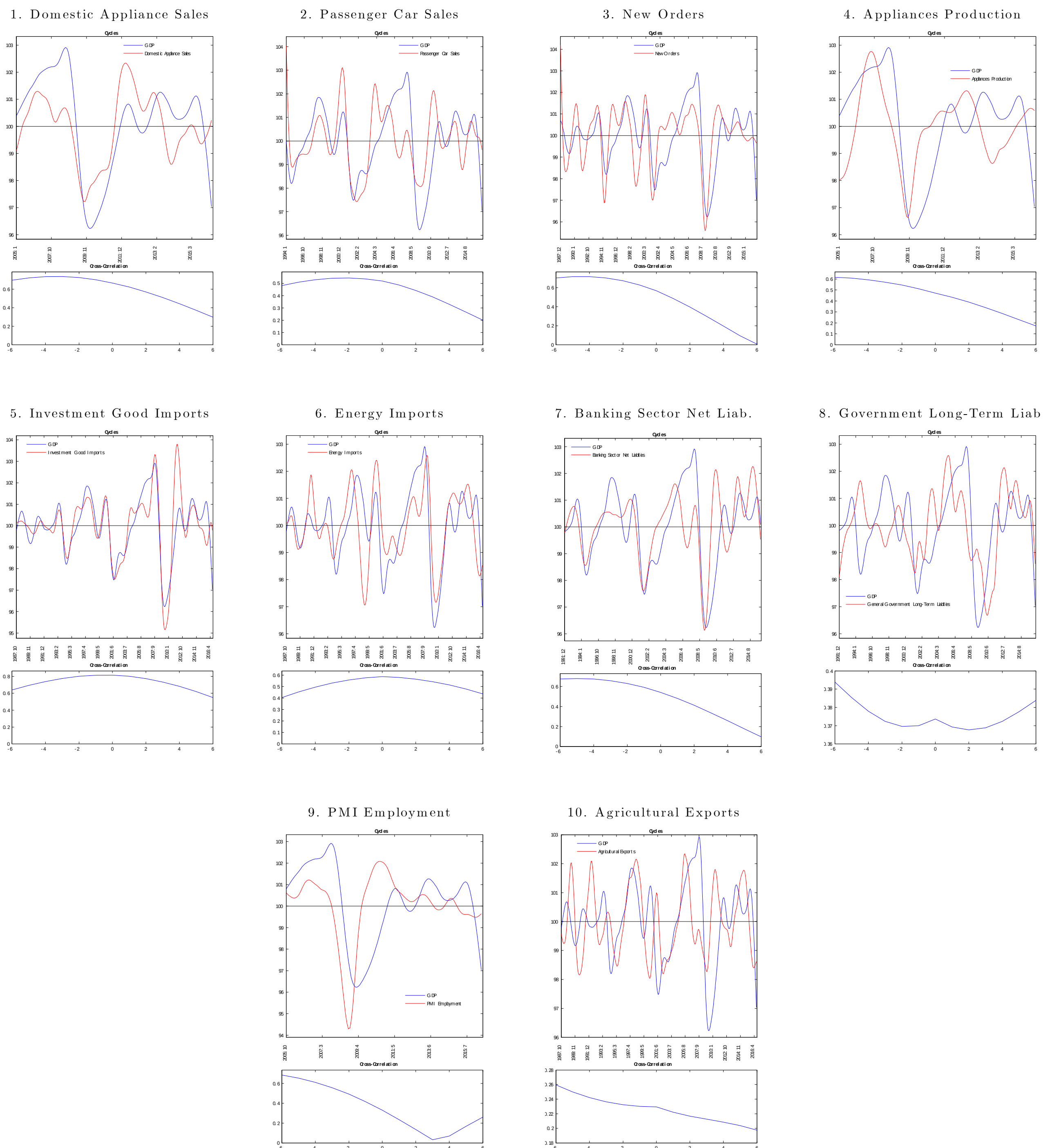


Figure 9. The Composite Leading Indicator

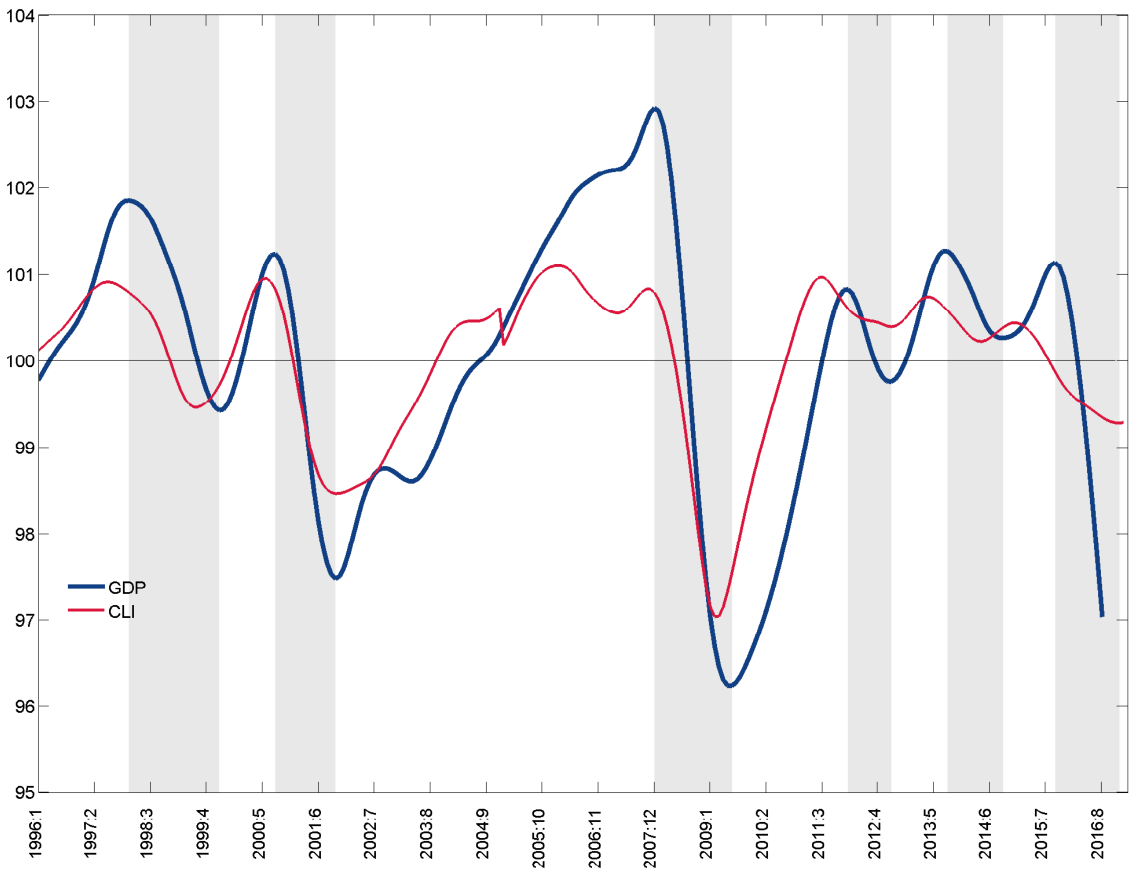


Figure 10. Cross-Correlation Function of the CLI

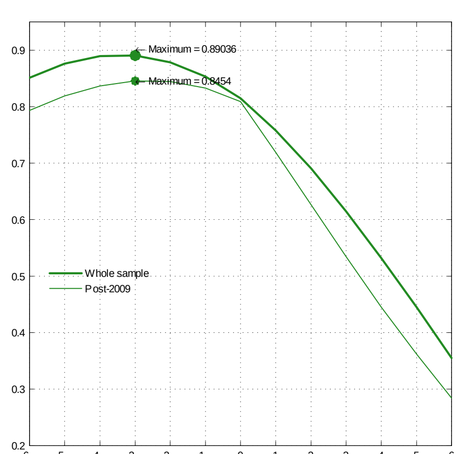


Figure 11. A Steep and Deep Cycle

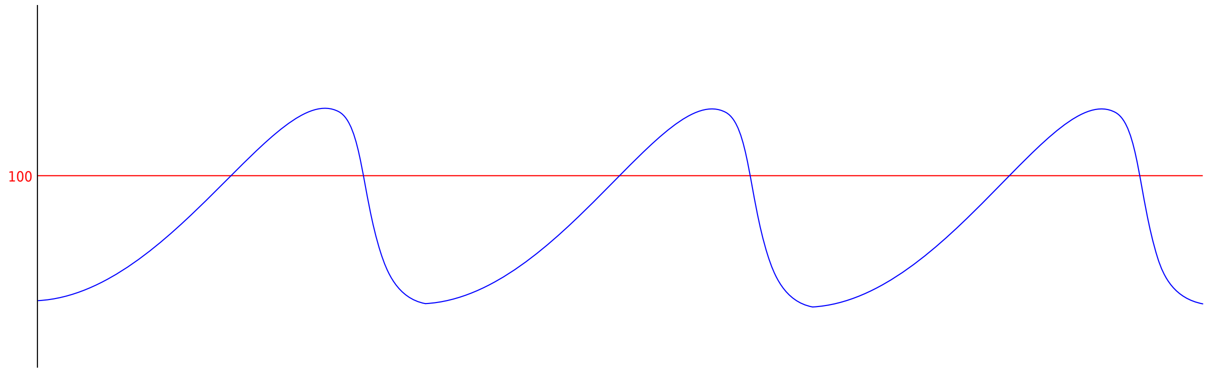


Figure 12. Calculation of A-Priori Trough Probability, Γ^{τ}

$$\Gamma^{\tau} = \Pr[z_T + \mu_{\Delta z^e} - \zeta^{\tau}\sigma_{\Delta z^e} < z_{T+1} < z_T + \mu_{\Delta z^e} + \zeta^{\tau}\sigma_{\Delta z^e}]$$

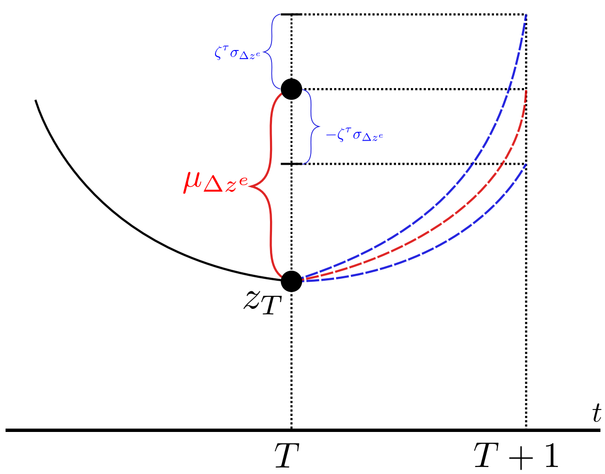


Figure 13. Comparison of Sequential Probabilities-I

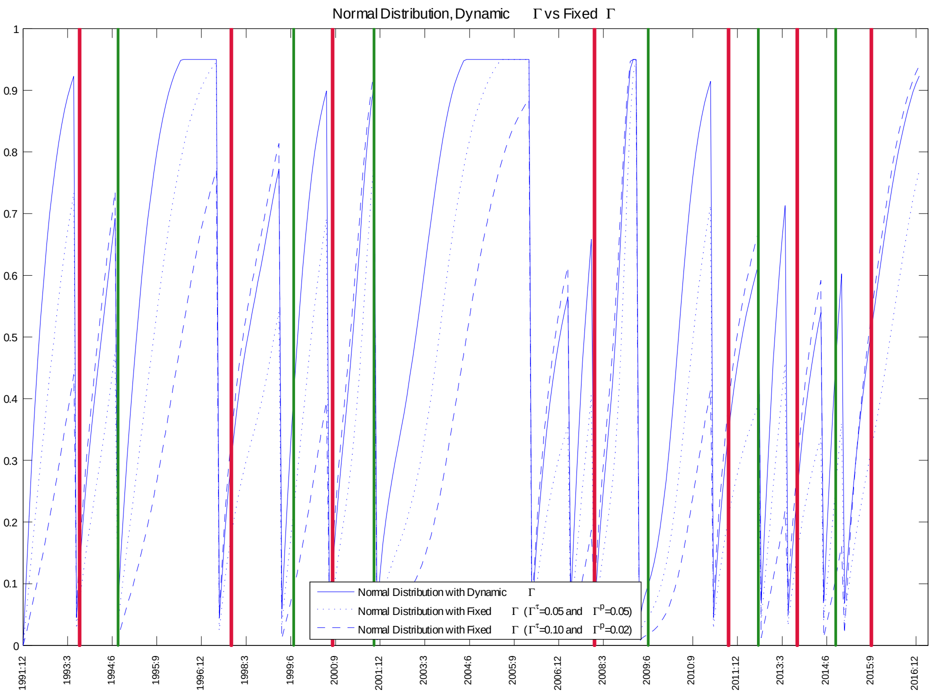
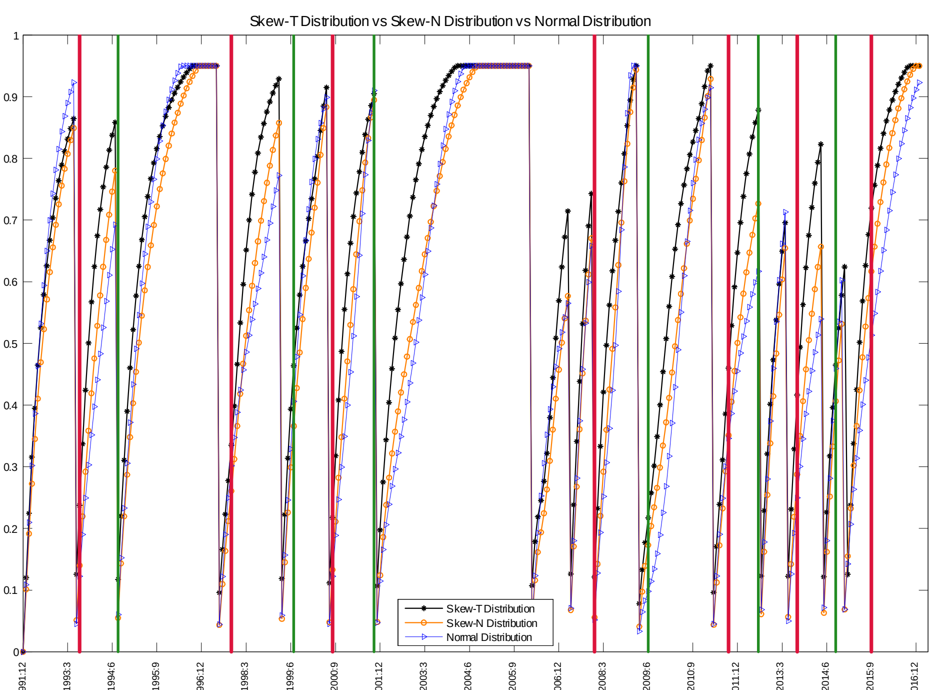


Figure 14. Comparison of Sequential Probabilities-II



Tables

Table 1. The implications of alternative filters about the potential GDP

	Average growth rate of the potential output (%)	Persistence of fitted process	Standard deviation of fitted residuals
Double HP	4.39	0.944	0.0180
Classic HP ($\lambda = 14400$)	4.35	0.996	0.0299
Classic HP ($\lambda = 129600$)	4.42	0.995	0.0163
Baxter-King	4.29	0.976	0.0353
Christiano-Fitzgerald	4.50	0.942	0.0208

Table 2. The characteristics of recent crises

	1993-1994 Banking Crisis	1997 Russian Crisis	2001 Crisis	2007 Global Financial Crisis
Total decline in economic activity (%)	2.85	2.43	3.75	6.68
The extent of trough (%)	1.80	0.58	2.52	3.77
Duration of downturn (months, peak to trough)	13	21	14	18
Duration of upturn (months, trough to peak)	38	13	74	27
Duration from trough to potential (months)	20	6	34	21
Time under potential (months)	27	11	42	31

Table 3. The leading performance of the CLI around GDP Turning points

GDP TP dates		CLI TP dates	Leading time (months)
1993:07	Peak	1993:05	2
1994:08	Trough	1994:07	1
1997:10	Peak	1997:05	5
1999:07	Trough	1999:02	5
2000:08	Peak	2000:06	2
2001:10	Trough	2001:10	Coincidental
		2006:02	False signal
		2007:03	False signal
2007:12	Peak	2007:11	1
2009:06	Trough	2009:02	4
2011:09	Peak	2011:03	6
2012:07	Trough	2012:07	Coincidental
2013:08	Peak	2013:04	4
2014:09	Trough	2014:04	5
2015:09	Peak	2014:12	9

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