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A New Approach to the Evaluation and Selection of Leading Indicators

Andreas Gottschling and Thomas Trimbur

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Abstract

Leading indicators are typical constructs used in macroeconomics to guide decision making in several areas of economic activity, including policy formation and long term investment. Researchers often evaluate and select leading indicators on a seemingly ad hoc basis involving OLS regression, which does not take into account the fact that perhaps the most important property of a good leading indicator lies in its ability to anticipate the turning points of the time series of interest. We propose an alternative assessment of leading indicators, based on the turning point significance transform, which weights each observation of the original time series according to how much it functions as a turning point. This new construct is then used to evaluate the accuracy and timeliness of several German and American macroeconomic time series as leading indicators for GDP growth.

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Keywords: leading indicator, turning point, prediction

Andreas Gottschling, Deutsche Bank Research, Grosse Gallusstrasse 10-14, 60272 Frankfurt, Germany

Email: andreas.gottschling@dbresearch.deuba.com

Thomas Trimbur, Deutsche Bank Research, Grosse Gallusstrasse 10-14, 60272 Frankfurt, Germany

Email: thomas.trimbur@dbresearch.deuba.com

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I. Introduction

A leading indicator refers to an economic variable which tends to anticipate another quantity at a certain lag. For example, the value of housing starts in the current period might help one to predict the growth of real GDP in future quarters. Leading indicators can also represent a composite of economic variables. Such indices typically consist of proxies for consumer sentiment and for various forms of investment, among other things. Researchers have typically used leading indicators for a wide variety of applications and have incorporated them into economic forecasting in many ways. Box and Jenkins [1994] discuss the use of leading indicators in conjunction with auto-regressive and moving average terms to improve forecasting performance. Perez [1996] analyses a regime switching model in which the state probability transitions depend upon a composite index leading indicator. Given that the use of leading indicators is pervasive in both academic research and in practice, it is surprising that these variables are often selected and evaluated on a seemingly ad hoc basis which neglects their usual purpose.

Specifically, a methodology based on OLS is typically employed to analyse potential leading indicator candidates and to select the appropriate lag for an acceptable variable. OLS obtains the best linear fit at each lag by minimising the sum of squared errors and in weighting each error equally, does not take into account the fact that leading indicators are supposed to anticipate turning points. In practice, researchers often determine the utility of a leading indicator by how well it predicts major transitions. It is conceivable that we may find an economic variable which performs well in gauging the turning points of a series but does not do well in trend-dominated regions. While the minimum sum of squared errors achievable with a linear transformation of the variable might be so large that OLS rejects the quantity as a leading indicator, we may not want to dismiss it so easily in practice.

To establish a criterion for how well a given economic variable anticipates the turning points of another, we must first elucidate the precise concept of what constitutes a turning point. Many researchers have apparently taken the concept for granted and assumed that major turning points were obvious by inspection, but some have attempted to define the notion more rigorously. For example, Stock and Watson [1989], analysing US real GNP growth, labelled each sequence of two consecutive quarters of negative growth as a turning point. Hamilton[1989] and Perez [1996] defined a turning point as a discrete regime shift.

The common aspect among these frameworks is that they all presuppose a binary labelling scheme. That is, each observation or sequence either represents a turning point or does not. Depending upon the application, this convention can fail to use all the information provided by the finite sample in an efficient manner. In a binary labelling scheme, one does not discern among the observations labelled as turning points although they might differ substantially in significance. Similarly, observations on the border which a binary scheme leads us to marginally reject as turning points might nonetheless mark somewhat influential periods of transition.

To deal with this sort of limitation, we construct a time series referred to as the turning point significance, which intuitively gives the degree to which each observation in a finite sample behaves as a turning point. We define this time series and discuss some of its characteristics in section 2. Section 3 proposes an alternative linear estimation scheme based on minimising a weighted sum of absolute errors, with each error weight related to the turning point significance of the time series of interest in each period. We show in a few examples how the linear fit obtained in this manner allows the leading indicator series to capture the turning points more precisely at the expense of accuracy in trend dominated regions.

Using the same weighting scheme which focuses on major turning points, in section 4 we construct a test for how well a given leading indicator performs in anticipating critical trend reversals. This scheme will in general produce different results from one in which OLS regression is employed in determining the appropriate lag and strength of the leading indicator. We compare the two testing methodologies using several examples of proposed leading indicator relationships in German and American economic data. Finally, section 5 concludes and discusses issues relevant to future research.

II. Turning Point Significance

Given a finite sample of a time series, one can note by observation that certain points appear to act as peaks while others function as troughs. Such observations constitute the apparent turning points of the series. However, upon further reflection, one notes that this concept is clearly horizon dependent. In financial forecasting, prediction of an economic variable one year ahead entails a different process from prediction 3 months into the future, and in some ways, it makes no sense to speak of forecasting without specification of the horizon. Likewise, the analysis of asset returns depends crucially upon the assumed time interval. In fact, a researcher investigating annual stock returns might use an entirely different model for dealing with daily or weekly data.

Whether a certain point in a time series represents a turning point and to what degree depends upon the horizon of interest. In figure 1 below, the observation in period 13 represents an apparently significant turning point on a 6 period horizon(that is, looking 3 periods back and 3 periods ahead), but constitutes a less significant transition when viewed on a 24 period horizon(looking 12 periods back versus 12 periods ahead).

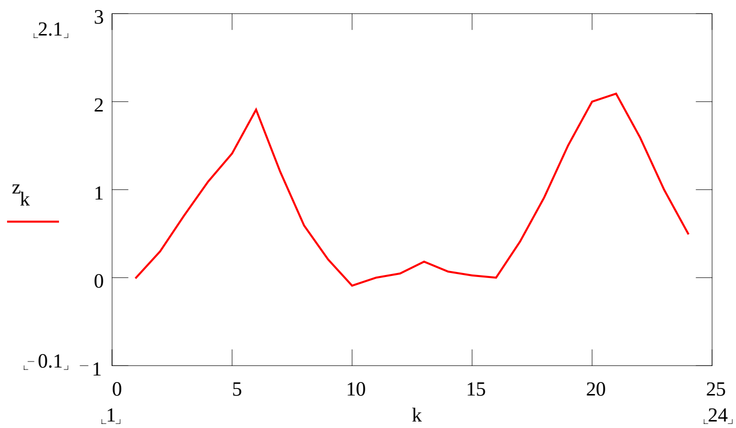

Figure 1: Turning point significance depends upon horizon.

One can construct several examples to clarify this concept, but the point is that the concept of a turning point implicitly assumes a specific time horizon.

Given the horizon of interest, a related issue involves the determination of what constitutes a significant turning point. Rather than employ a simple scenario under which each observation in a finite time series sample either represents a turning point or does not, we define a concept referred to as the turning point significance, or TPS. Given the horizon of interest, the TPS will provide a quantitative measure of how much each observation behaves as a turning point. This function explicitly incorporates the ambiguity and uncertainty inherent in the assessment of turning points in a finite time series sample. In addition, the TPS provides a convenient form for use in a linear estimation framework.

Given a time series $\{Y_t\}$, t = {1,2,...,T} and a horizon of interest F (assumed to be an even integer), we construct a time series $\{TPS_t\}$, t = {1,2,...,T} in the following manner:

$$TPS_t = 0, \text{ for } t = \{1,2,...,F, (T-F+1), (T-F+2),...,T\} \qquad (1)$$

These initial and final values of the TPS series are set to zero because the finite time series sample of size T does not consist of sufficient information to assess the turning point significance of these observations. Clearly this manner of dealing with the beginning and end of the series represents an inefficient use of the available information, but the current convention provides a basic starting point. Next construct a weight vector whose elements are given by a piecewise linear function of the index. First, define the piecewise linear function P(x):

$$P(x) = \begin{cases} x/F & \text{if } 0<x<F/2 \\ (F-x)/F & \text{if } F/2<=x<F \\ 0 & \text{otherwise} \end{cases} \qquad (2)$$

Then, define the F element vector W as:

$$W_i=P(i),\ i=1,2,...,F \qquad (3)$$

Now, we construct a deviations matrix which consists of F elements for each of the T-2F core observations ranging from t=F+1 to t=T-F. Each element of the (T-2F)xF matrix D equals:

$$D_{j,i}=(|y_{j+F}-y_{j+F-i}|+|y_{j+F+i}-y_{j+F}|)\cdot|(y_{j+F}-y_{j+F-i})-(y_{j+F+i}-y_{j+F})| \qquad (4)$$

Finally, we obtain the remaining elements of the turning point significance time series:

$$TPS_{(F+1),\ldots,(T-F)} = (D)(W) \qquad (5)$$

where $TPS_{(F+1),\ldots,(T-F)}$ denotes the vector consisting of the values of TPS_t for t ranging from (F+1) to (T-F) in the appropriate order.

As an example, consider the time series of 70 observations plotted in figure 2. A positive multiple of the TPS time series for a horizon of 6 periods is displayed in the same graph. Note that the events which a casual observer might select as major turning points correspond to a relatively high value of TPS, and likewise, those observations which appear to lie in a region dominated by a trend coincide with a lower value of TPS. In this example, the TPS agrees with one’s intuition concerning what should constitute a major turning point. However, this time series also provides a quantitative assessment of exactly to what degree every other observation behaves as a significant turning point.

The TPS time series constructed in the above manner appears to have some appealing features. First, only linear components were utilised in its design, and thus this variable represents perhaps one of the most elementary constructions which can assess a concept such as turning point significance in a satisfactory manner. Secondly, the convenient form allows for straightforward use in estimation procedures. In the next section, we turn to the comparison of OLS with the alternative scheme using a few examples.

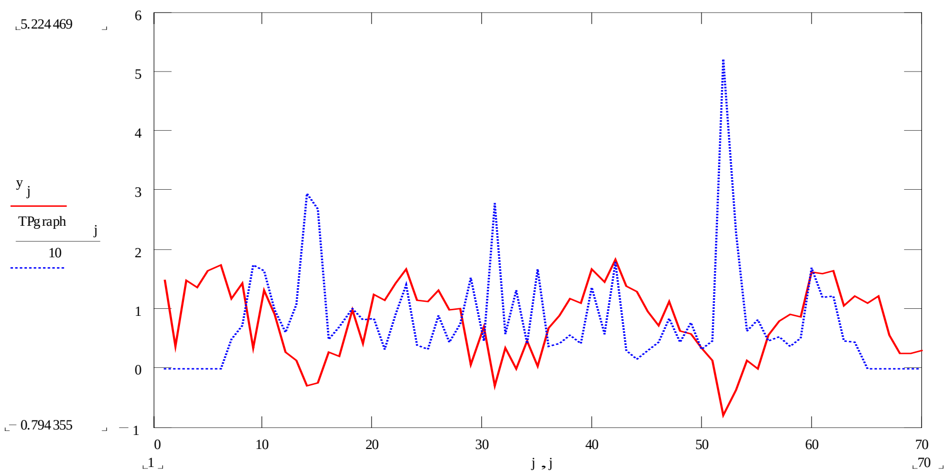

Figure 2: Time Series plotted with TPS

III. Estimation Using the TPS Time Series

Using the ordinary least squares criterion in a linear framework, the coefficient and constant parameters are estimated by minimising the sum of squared deviations. Specifically, given a time series of interest Y_t, and a predictor time series $Z_t(=X_{t-k}$, where X is a leading indicator for Y at lag k), we wish to determine the most suitable choice for the parameters ψ and γ in the following equation:

$$Y_t = \psi + \gamma Z_t \qquad (6)$$

OLS proceeds by finding ψ and γ which minimise:

$$SSE(\psi,\gamma) = \Sigma(Y_t - \psi - \gamma Z_t)^2 \qquad (7)$$

As mentioned above, this estimation method weights all errors according to the same criteria, regardless of how important the particular observation is. In addition, large errors are punished severely under this framework, and thus one or two extreme observations can have an unduly large impact.

According to the alternative estimation scheme, the following weighted sum of absolute errors, WSAE(ψ,γ), is minimised to select the two parameters:

$$WSAE(\psi,\gamma) = \Sigma TPS_t|Y_t - \psi - \gamma Z_t| \qquad (8)$$

TPS_t refers the value at time t of the turning point significance for Y, the series of interest. Therefore, we explicitly weight the absolute error of an observation by the turning point significance at that time. By construction, the predicted values of Y_t will correspond more closely to the actual values for observations which behave like major turning points. We use absolute errors partly because the danger of over-fitting to extreme observations increases when the errors are weighted by the corresponding turning point significance. Specifically, outliers will likely possess high TPS values so that we expect these two characteristics to be correlated to some degree.

For the first example, we construct two time series according to:

$$Z_t = \sin(t/2),\ t = 1,2,...,T,\ T = 70 \text{ observations} \qquad (9)$$

$$Y_t = 0.8 + 0.7Z_t + \varepsilon_t, \text{ where } \varepsilon_t(\text{i. i. d}) \sim N(0,0.3)$$

This scenario represents a case where the predictor variable Z (which equals the leading indicator already lagged) consists solely of a cyclical component, and the variable of interest Y is determined by a linear function of Z plus an independent and identically distributed normal error term. A positive multiple of the TPS (F = 6) time series is displayed along with Y in the plot of figure 3.

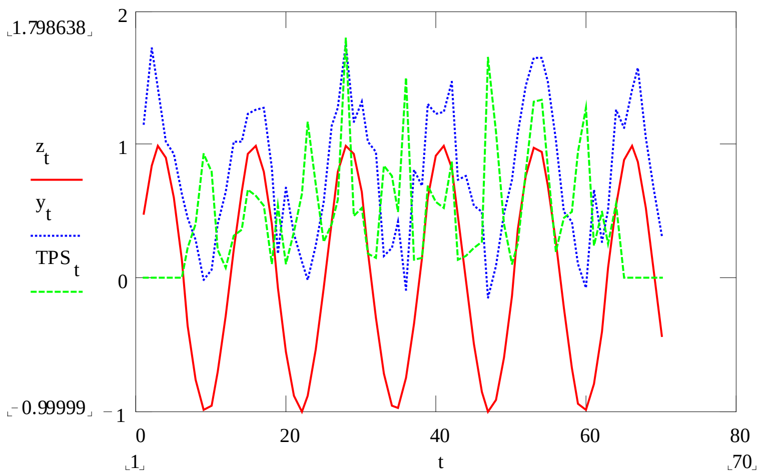

Figure 3: Cyclical Time Series Plotted with TPS.

Upon determination of the most appropriate linear fit according to the OLS and TPS weighting schemes, one obtains significantly different parameter estimates. The OLS results give $\psi_{OLS} = 0.763$ and $\gamma_{OLS} = 0.664$, while the TPS-weighted results show that $\psi_{TPS} = 0.803$ and $\gamma_{TPS} = 0.833$. The OLS coefficient estimate lies closer to the actual value of 0.7 specified in the data generating process, and this fact should not surprise us since the construction of the data utilised an i. i. d. normal error process, for which OLS estimators perform best. Whether or not real world economic and financial data are generated by such a simple mechanism represents a separate issue. For data generating processes which contain smaller errors near turning points, the TPS estimator will perform more suitably according to bias and efficiency criteria.

One can gain insight into the nature of the alternative estimation scheme by graphically comparing the OLS and TPS linear predictions. Figure 4 below displays the original series along with the two alternative linear fits, and it is apparent that the TPS estimates perform better in capturing the behaviour surrounding the periods of transition.

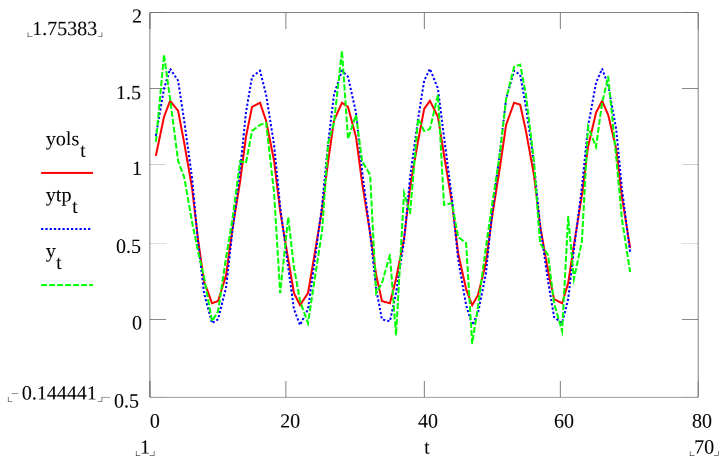

Figure 4: Original Series versus OLS and TPS predictions.

However, the TPS estimates miss badly in some places. In particular, OLS provides a fairly accurate approximation of the level of the second peak, whereas the TPS estimate lies far above the actual data. For the third trough, the TPS fit characterises the depth of the decline with reasonable accuracy, but the actual series hits the bottom later than anticipated. In addition, because of the specialised weighting scheme, OLS typically performs better when the time series is rising or falling in a trend-like pattern.

As a second example, we consider a repeated slow rise-crash pattern:

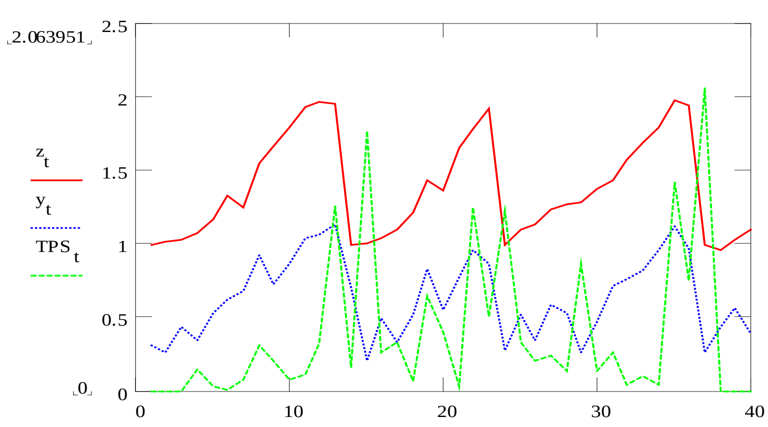

Figure 5: Slow rise-crash time series plotted with TPS

During each phase, the leading indicator time series Z initially increases gradually, then accelerates, tapers off, and finally collapses. We generate Y in terms of Z in the following manner:

$$Y_t = -0.85 + 0.7Z_t + \varepsilon_t, \text{ where } \varepsilon_t \sim \text{i. i. d } N(0,0.1) \qquad (10)$$

In constructing the TPS time series for this case, we employ a horizon of interest(F) equal to 3 periods rather than 6 because the crucial sharp plunges occur on such a short time scale. Once again, we obtain significantly different coefficients depending upon which weighting scheme is used. The least squares results give ψ_{OLS} = -0.803 and γ_{OLS} = 0.647 while the alternative method produces ψ_{TPS} = -1.037 and γ_{TPS} = 0.812. The OLS estimates lie closer to the actual values used to construct the data partly because of the assumption of independent and identically distributed normal errors. However, when one inspects the graph in figure 6 below, one notices that the TPS weighted scheme performs slightly better in modelling the behaviour of Y near the crashes. In contrast, OLS produces more accurate approximations in general during the slow rises leading up to the sudden declines.

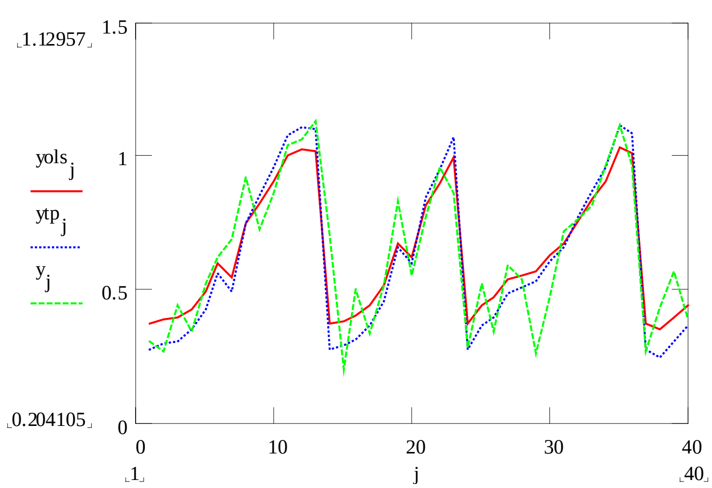

Figure 6: Slow rise-crash time series with OLS and TPS fits

These examples give insight into what one can accomplish by using the turning point significance time series in a linear estimation framework. Since we restrict the analysis to a linear form, we cannot possibly improve the timing of a given leading indicator. TPS predictions equal an affine transformation of OLS predictions, and thus, they will increase and decrease in tandem. However, these TPS predictions clearly perform better in gauging levels near important turning points at the expense of accuracy in trend-dominated regions. During a prolonged unidirectional movement, TPS fitted values will change too slowly or too quickly and will be prone to stray away from the trend line. In contrast, these estimates will on average assess the levels around major turning points far better than OLS.

Recall that above we have utilised absolute errors rather than squared errors in constructing the TPS-weighted estimates. In general, the least squares framework can fall into the trap of over-fitting to a few extreme observations since outliers are punished so severely. I mentioned above that using a TPS-weighting scheme can potentially intensify this problem because an outlier is likely to possess a high TPS value. Thus, when we square the error and then in addition multiply by the TPS, we might perhaps give an inordinate amount of weight to only a few extreme observations.

Despite this potential difficulty, we base the testing methodology in the next section on weighted least squares because of the simplicity of the development and the natural comparisons with OLS which result from this assumption. In addition, we use the turning point significance of the leading indicator time series rather than the time series of interest. This leads to an intuitive definition of a TPS leading indicator as a leading indicator which assesses the turning points of a designated time series successfully, and one can test whether X leads Y in a turning point significant way by applying a version of weighted least squares to the data.

In the next section, we formulate the definition of a TPS leading indicator and construct a test for whether or not a given variable functions as a TPS leading indicator for another over a given finite sample. Next, we show in an example how this framework can have different implications than OLS for the optimal lag of a leading indicator, given that we focus on sharp movements of the time series of interest. Finally, we proceed to test eight pairs of time series relating to German and American economic data, and make comparisons with a methodology based on OLS estimation.

IV. Turning Point Significant Leading Indicators

This section defines the concept of a turning point significant, or TPS, leading indicator and proceeds to test several pairs of commonly used macroeconomic time series to determine whether or not they satisfy this relation. In practice, leading indicators are typically implemented using rules of thumb, and OLS estimation is utilised to determine the effects of the leading indicator on the time series of interest, to choose the appropriate lag, and to aid in forecasting. In the last section, we demonstrated with a few examples how an error weighting scheme based on turning point significance can produce linear parameter estimates which lead to improved accuracy around turning points. Now, we define a TPS leading indicator as a time series which predicts the series of interest with a smaller error near turning points.

Definition: Given two time series samples of length T, Y_t(the series of interest) and Z_t(=X_{t-k}, where X is proposed to lead Y at lag k), we say that X acts as a turning point significant, or TPS, leading indicator for Y_t at lag k for a horizon of interest F if the following data generating process establishes Y_t for some constants ψ, γ, and σ^2, with γ nonzero:

$$Y_t = \psi + \gamma Z_t + \varepsilon_t, \text{ where } \varepsilon_t \sim N(0, \sigma^2/TPS_t) \qquad (11)$$

In this definition, Z_t is assumed entirely exogenous, and TPS_t refers to the turning point significance time series of Z_t for a horizon of interest F.

Thus, Y_t is given by a linear function of Z_t with a normally distributed error with zero mean and standard deviation inversely proportional to the square root of TPS_t. Intuitively, the more Z_t exhibited turning point characteristics at time t, the more accurate is the linear prediction of Y_t. The definition does not refer to the forecast error variance of Y_t given X_{t-k} or to the one step ahead forecast error of Y given values of X in the previous period and before. Rather, it removes these issues from consideration by assuming complete exogeneity of Z_t. The resultant test for a TPS leading indicator should be regarded as entirely ex post.

Multiplying the specification by $TPS_t^{1/2}$ on both sides, we obtain:

$$Y_t TPS_t^{1/2} = \psi TPS_t^{1/2} + \gamma TPS_t^{1/2} Z_t + TPS_t^{1/2} \varepsilon_t \qquad (12)$$

Given the assumption of exogeneity of all observations on Z_t, we immediately have that $TPS_t^{1/2}$, constructed as a function of this time series, is also exogenous.

We wish to perform a test of the null hypothesis that $\gamma = 0$, which means that Z_t is not a TPS leading indicator for Y_t, against the alternative hypothesis that γ is in fact nonzero. Since $TPS_t^{1/2}$ is exogenous, we have that:

$$Var((TPS_t)^{1/2}\varepsilon_t) = TPS_t Var(\varepsilon_t) = TPS_t(\sigma^2/TPS_t) = \sigma^2 \qquad (13)$$

Therefore, performing OLS with the data weighted by $TPS_t^{1/2}$ results in an efficient, unbiased estimate for γ. Under the null hypothesis that $\gamma = 0$, the estimated coefficient γ_{TPS} divided by the standard deviation of the estimate possesses a t distribution with the appropriate number of degrees of freedom. The current situation essentially represents a case of weighted least squares, and we test the null hypothesis that X is not a TPS leading indicator for Y at lag k by comparing the estimated t ratio of γ_{TPS} to the corresponding critical value of the proper t distribution.

Given a time series of interest Y_t and a series X_t which is proposed to lead Y_t, we compute the optimal lag based on OLS, k_{OLS}, by selecting the lag(from a specified range) which produces the highest R^2 in a standard regression of Y_t on X_{t-k}. Likewise, we determine the optimal lag according to TPS by running the above weighted least squares regression for several lag values over a reasonable range, and selecting that value which produces the highest R^2. The optimal lag obtained in this manner, k_{TPS} will not in general equal the optimal lag generated by OLS, k_{OLS}. Thus, it becomes conceivable that a predictor variable which performs well at lag k in terms of the non weighted regression R^2 fails as a TPS leading indicator, and thus does not gauge the turning points of the time series of interest accurately.

As an example of a case in which the two methods lead to divergent conclusions, consider the two artificially constructed time series in the plot below.

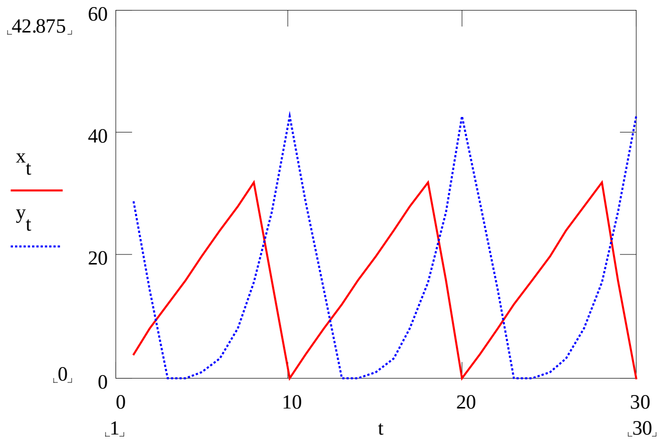

Figure 7: Leading Indicator X anticipates sharp declines in Y by two periods.

We see that X, which is constructed entirely from linear segments, reaches a peak exactly two time periods before Y, which is composed of both cubic and linear portions. However, Y begins its gradual ascent three periods after X recovers. Thus, it is not clear a priori what the optimal lag of the leading indicator should be, and furthermore, the value obtained by a specific evaluation scheme will depend on how much emphasis the procedure places on the timing of the sharp plunges as opposed to the recoveries. Table 1 shows the results of using the OLS versus the TPS methodology to determine the significance of X in predicting Y at each lag, in terms of the coefficient t statistic and R^2.

Table 1: OLS and TPS results for example in figure 7.

K	T_{OLS}	R^2_{OLS}	T_{TPS}	R^2_{TPS}
1	0.608	0.014	0.303	0.00339
2	5.571	0.544	6.22	0.598
3	10.619	0.819	2.629	0.217
4	5.161	0.526	0.409	0.00691
5	1.690	0.110	1.033	0.044

Using OLS regression with the original data, the R-squared and t statistics reach a peak when the estimation is performed using k = 3, but the regression using the data weighted by the square root of the turning point significance produces the highest R-squared and t-statistic for k = 2. Thus, the two schemes imply different optimal lags, and in fact, the TPS weighted scheme models the timing of the sharp declines more accurately. The series of interest Y is plotted with the leading indicator X lagged by two and three periods in figure 8.

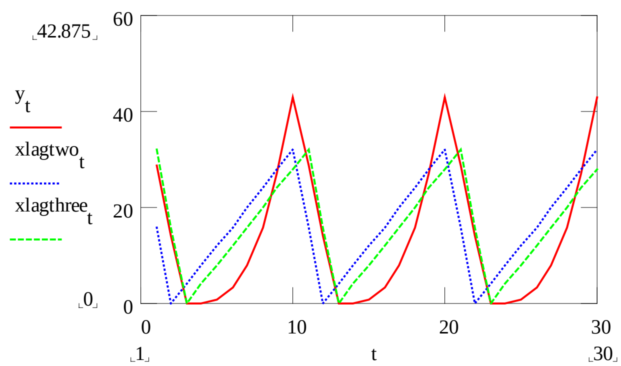

Figure 8: Series of interest (Y) plotted with leading indicator (X) at lags of two and three periods.

We now proceed with the novel testing methodology and comparison with OLS for several examples involving real economic data. For each lag k within a certain range, we determine the t ratio of the linear coefficient and the R^2 resulting from OLS regression of Y_t on X_{t-k}. Likewise, we compute these two statistics for a regression with weighted data values, where the weight at each time period equals the square root of the TPS of the lagged leading indicator at time t.

The eight examples for an initial evaluation using quarterly data from Q1 1970 to Q4 1994 are obtained from the Deutsche Bank Research economic database. The IFO business climate index and the year on year change (% year on year) in the number of new non residential housing permits in Germany are each proposed to lead the year on year change in German real GDP. Similarly, we examine how well the OECD leading index trend for the German economy (% year on year) and labour productivity (% year on year) lead economic growth. For these cases, we omit the four quarterly observations biased by reunification accounting effects. Using US economic data, we propose the number of housing starts each quarter and the National Association of Purchasing Managers (NAPM) composite diffusion index as leading indicators for real GDP (% year on year) in the US. Likewise, the OECD leading index trend (% year on year) and manufacturing productivity (% year on year) are analysed as leading indicators for economic growth.

Tables A1 through A8 in the appendix of the paper display empirical results for the OLS and TPS-weighted regressions. To produce the alternative estimation results, we weight each error by the square root of the value of the TPS time series of the lagged leading indicator in the appropriate period. Each of the tables corresponds to a specific time series of interest – leading indicator pair, and we estimate the regressions for lags ranging from 1 to 5 periods (except for US manufacturing productivity (% year on year), for which OLS obtains an optimal lag of 6 quarters in anticipating economic growth). For each lag, we display the t ratio and R-squared resulting from OLS estimation, as well as the corresponding values generated by a regression using weighted observations. The critical value for rejecting the null hypothesis of a zero coefficient at the 1% level of significance equals approximately 2.64 since we have about 90-100 observations in each regression.

The results in Table A1 indicate that both OLS and TPS agree that the number of non residential housing permits (% year on year) approximately leads German real GDP growth at a lag of 3 quarters. At a lag of three quarters, the estimated t ratio exceeds the 1% critical value of 2.64 according to the TPS scheme and surpasses the 5% critical value for OLS, and the R-squared values peak at this lag for both methods. Thus, this leading indicator performs well both from a standpoint of minimising the sum of squared errors and for the purpose of gauging turning points. It is interesting to note that the estimated t ratios and R-squared fall off more rapidly upon deviation from the optimal lag when using the TPS scheme.

According to Table A2, the IFO business climate index fails to serve as a TPS leading indicator at any of the tested lags for a 5% level of significance while OLS estimation produces significant t ratios for lags 1 to 3. In fact, the highest t-ratio for the TPS method of 1.814, obtained with a lag of one period, falls below 1.98, which marks the critical value corresponding to a 5% level of significance. Although one can find a linear function of the lagged index which performs well in minimising the sum of squared errors, there is no linear transformation which accurately assesses the turning points according to our framework. Tables A3 and A4 show that the two schemes imply that both the OECD leading index trend (% year on year) and productivity (% year on year) act as leading indicators for German real GDP growth at the first few lags, with the first one optimal. Table A5 indicates that the quantity of total quarterly housing starts in the US leads US economic growth at the first lag although the OLS results imply that this relationship is more significant than does the TPS estimation. In Table A6 (NAPM composite diffusion index), we see that while OLS estimation results in significant t ratios from lags 1 to 3, TPS accepts the null hypothesis of no relationship at all lags examined. Thus, OLS implies the clear acceptance of the NAPM composite diffusion index as a leading indicator, but the turning point significance framework does not. Table A7 shows that both OLS and TPS imply that the OECD leading index trend

(% year on year) serves as a leading indicator for US economic growth, yet the t ratios fall off more sharply at higher lags under the TPS framework. Finally, in Table A8 we find that according to the TPS scheme, productivity impacts growth for the most part with a lag of three quarters, but the coefficient estimate falls short of being significant at the 1% level. On the contrary, OLS implies that productivity acts as a highly significant leading indicator at a lag of six quarters.

In several cases, using the turning point significance framework to analyse potential leading indicators has resulted in implications similar to those of OLS. Both methods lead us to conclude that the year on year changes in non residential housing permits, the OECD leading index trend, and labour productivity all act as significant leading indicators for German economic growth. Likewise, the yoy changes in the OECD leading index trend for the US economy and the number of quarterly housing starts both function as leading indicators for US economic growth according to the methodologies.

However, several important differences become apparent when we examine the various tables. First, the strength of each leading indicator, as gauged by the t ratio and R-squared, occasionally differs between the two frameworks. According to table 5, the R-squared for OLS and TPS estimation using total housing starts lagged by 1 quarter is 0.52 and 0.09, respectively, indicating that OLS attaches much more power to this quantity in leading economic growth. Second, the two schemes disagree substantially on the optimal lag in the case of US manufacturing productivity (% year on year) and on how significant this leading indicator is at the optimal lag. Finally, in a few cases, OLS estimation accepts as a highly significant leading indicator a variable which the TPS scheme rejects at the first five lags.

V. Conclusions

We have constructed a time series giving the degree of turning point behaviour at each period, and have used this quantity to calculate an alternative estimator for the linear prediction of a time series using an appropriate lagged leading indicator. The method essentially weights the error for each observation by a quantified measure of how much the series exhibits turning point behaviour at that time. Thus, the leading indicator is forced to perform better near apparent turning points at the expense of accuracy in trend-dominated regions.

Based on a data generating process in which errors decline near major turning points, we have used the turning point significance time series to construct a simple test for the ability of a proposed leading indicator to gauge the critical transition periods of a particular time series. The methodology determines the performance of the leading indicator in this regard at each lag and thus allows one to select the optimal lag. We have shown in an artificially constructed example that the alternative scheme can improve the timing of the leading indicator in anticipating sharp changes in the time series of interest.

We have utilised the turning point significance in testing several leading indicators in anticipating major changes in German and US real GDP growth. The results have quite interesting implications partly because two time series which are typically thought to function as accurate leading indicators do not, in fact, capture major turning points as determined by our special criteria. This includes the IFO business climate Index for German economic growth and the Purchasing managers composite diffusion index for US economic growth. In other cases, the results differ concerning the appropriate lag and the strength of the leading indicator.

This preliminary investigation has produced some interesting results and has demonstrated that the new TPS methodology does not in general coincide with the typical OLS-based decision strategy. Whether or not this novel framework will prove more useful in general remains uncertain. The definition of a TPS leading indicator and the test which follows naturally hinge critically upon the definition of the turning point significance time series, which involves a new perspective on what it means for an observation to be a turning point. Specifically, the convention of giving a yes/no answer to the question of whether a given observation constitutes a turning point is replaced by the construction of a measure which rates every single point in the finite sample according to how much it behaves as a major turning point. This new perspective entails using the generalised notion of turning point significance instead of separating the sample into non turning points and turning points. We expect that given a finite sample, the observations which appear to constitute the primary turning points upon casual inspection will also coincide with maximum values of the turning point significance time series in general.

The use of the turning point significance concept stands in contrast to past approaches to the assessment of sharp changes in a time series. Many authors have used ad hoc definitions of what constitutes a turning point based on percentage changes in the series in surrounding periods. In addition, some researchers have considered turning points as discrete changes in regime. For example, Hamilton(1989) modelled the growth rate of US real GNP with a two state Markov regime switching model and interpreted the changes between the expansionary regime and the recessionary regime as the major turning points of this time series. All of these approaches have utilised a yes/no decision criterion to determine turning points. Such conventions possibly represent special cases of basing turning point selection on functions of the TPS. For example, if we use the TPS raised to the 4^{th} power to represent the importance of each observation in this regard, then the measures for the major turning points will exceed those of the insignificant turning points by so much that we will for all practical purposes have separated the sample into one group containing just a few critical turning points and a second group containing all other observations.

Whether the TPS framework we have developed in this paper will be amenable to out of sample forecasting poses a difficult question. The data generating process defining a TPS leading indicator as well as the test based upon this process assume complete exogeneity of the leading indicator time series. Thus, difficulties associated with forecasting are dismissed in favour of formulating a simple ex post test for leading indicator ability. Exactly how to extend the present analysis to produce forecasts which more effectively anticipate turning points warrants further investigation.

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Appendix

Tables

Table A1: Time Series of Interest - YOY change in German real GDP
Leading Indicator – YOY change in non residential housing permits

Lag	T_{OLS}	R^2_{OLS}	T_{TPS}	R^2_{TPS}
1	1.795	0.034	0.975	0.01
2	2.057	0.045	1.790	0.034
3	2.523	0.067	3.44	0.116
4	2.08	0.047	2.238	0.053
5	1.841	0.037	0.855	8.408E-3

Table A2: Time Series of Interest - YOY change in German real GDP
Leading Indicator - IFO Business Climate Index

Lag	T_{OLS}	R^2_{OLS}	T_{TPS}	R^2_{TPS}
1	6.579	0.391	1.814	0.035
2	5.132	0.274	1.759	0.036
3	3.474	0.143	1.376	0.023
4	1.879	0.044	0.262	8.416E-4
5	0.628	4.911E-3	-1.005	0.012

Table A3: Time Series of Interest - YOY change in German real GDP
Leading Indicator - YOY change in OECD leading index trend

Lag	T_{OLS}	R^2_{OLS}	T_{TPS}	R^2_{TPS}
1	6.476	0.318	11.175	0.576
2	5.831	0.278	5.097	0.223
3	4.49	0.189	2.823	0.082
4	2.658	0.077	1.465	0.025
5	1.057	0.013	0.238	1.535E-3

Table A4: Time Series of Interest - YOY change in German real GDP
Leading Indicator - YOY change in productivity

Lag	T_{OLS}	R^2_{OLS}	T_{TPS}	R^2_{TPS}
1	3.825	0.139	4.876	0.207
2	3.54	0.123	3.236	0.104
3	2.735	0.078	2.198	0.052
4	1.356	0.021	0.384	3.077E-3
5	0.4	2.442E-3	-0.213	2.44E-3

Table A5: Time Series of Interest - YOY change in US real GDP
Leading Indicator - Total Housing Starts

Lag	T_{OLS}	R^2_{OLS}	T_{TPS}	R^2_{TPS}
1	10.067	0.521	3.031	0.090
2	8.012	0.411	2.773	0.077
3	5.270	0.234	2.385	0.059
4	2.720	0.076	1.034	0.012
5	0.864	8.311E-3	-0.880	8.628E-3

Table A6: Time Series of Interest – YOY change in US real GDP
Leading Indicator – Purchasing managers composite diffusion index

Lag	T_{OLS}	R^2_{OLS}	T_{TPS}	R^2_{TPS}
1	12.19	0.615	1.615	0.027
2	7.603	0.386	0.884	8.422E-3
3	3.656	0.128	0.267	7.807E-4
4	0.695	5.346E-3	0.278	8.586E-4
5	-1.391	0.021	-0.747	6.235E-3

Table A7: Time Series of Interest – YOY change in US real GDP
Leading Indicator - YOY change in OECD leading index trend

Lag	T_{OLS}	R^2_{OLS}	T_{TPS}	R^2_{TPS}
1	14.526	0.694	10.149	0.526
2	11.11	0.573	4.608	0.188
3	6.995	0.350	1.050	0.012
4	4.240	0.166	-1.425	0.022
5	2.159	0.050	-1.855	0.037

Table A8: Time Series of Interest – YOY change in US real GDP
Leading Indicator – YOY change in productivity

Lag	T_{OLS}	R^2_{OLS}	T_{TPS}	R^2_{TPS}
1	2.142	0.047	-0.972	0.01
2	3.080	0.093	0.785	6.65E-3
3	4.751	0.199	2.250	0.053
4	5.955	0.283	2.104	0.047
5	7.025	0.357	1.976	0.042
6	7.168	0.369	1.784	0.035
7	6.080	0.298	0.550	3.467E-3
8	4.690	0.204	0.487	2.753E-3