TÜRKİYE CUMHURİYET MERKEZ BANKASI

WORKING PAPER NO: 13/33

Do We Really Need Filters In Estimating Output Gap?: Evidence From Turkey

August 2013

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DO WE REALLY NEED FILTERS IN ESTIMATING OUTPUT GAP?: EVIDENCE FROM TURKEY[1]

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Abstract

We estimate an output gap indicator for Turkey without resorting to any kind of a filtering procedure. Our approach stands on a two-step procedure: First, we pick such variables that are directly informative about the phase of the business cycle, where the decision of choice depends on their statistical and economic significance in estimated Phillips curves. Second, we model business cycles as the common driver of the selected variables and estimate it in a small scale dynamic factor model setting. In this way, we produce a filter-free measure of output gap, which proves to be superior to any other filter-based measure as being immune to end-sample revisions. Using up-to-date survey-based variables instead of filtered macroeconomic aggregates, we not only postulate a way of avoiding revision uncertainty embodied in statistical filters, but also meet the need for timely information as we deliver information on the cyclical position of the economy two-quarters in advance of the GDP.

Keywords: Output gap, statistical detrending filters, dynamic factor models, revisions in output gap estimates

Jel Classification: C32, E31, E32

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[1] The authors would like to thank an anonymous referee for helpful comments, and to Çağrı Akkoyun, Meltem Gülenay Chadwick and Mahmut Günay for their generous help in technical issues. The views expressed in this paper belong to the authors only and do not represent those of the Central Bank of the Republic of Turkey.
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1. Introduction

Output gap, the deviation of actual output from its noninflationary level, is a key ingredient of monetary policy making process in the inflation targeting framework. However, decomposing output into its unobserved components is not straightforward; it requires use of statistical filtering procedures, which have been open to several criticisms in the literature.[5] For instance, either augmented with economic information or not, filtering results suffer from end-point revision problems. When purely statistical filters are employed, trend estimates tend to track actual data, so backward revisions and arrival of new information may lead to significant changes in the potential output estimates. In the worst scenario for a decision maker, an output gap estimate for a certain period may call for contradictory policy moves (tightening vs. easing) at two different points in time. Besides, even when structural models are employed to incorporate economic information in the filtering process, end-sample problems may still stay alive. This major drawback constrains the use of output gap in real-time policy making and increases the need for robust indicators of cyclical pressures on inflation.

The primary objective of this study is to construct an output gap measure without any resort to any kind of a filtering procedure, yet by only using such indicators that directly contain information about the cyclical position of the Turkish economy. Rather than decomposing a certain measure of economic activity, i.e. Gross Domestic Product (GDP), into its permanent (trend) and transitory (cycle) components through statistical filters, aggregating such indicators that represent output gap itself is supposed be a remedy for the aforementioned end-point bias in filtering results. In that sense, widely referred statistics such as capacity utilization rate, working hours per worker can be put in the category of natural indicators of output gap, as by definition they contain pure information on the phase of the business cycle.

Following Lucas (1977), we think of the business cycle as a compound of several variables instead of representing it by a single measure of activity, i.e. capacity utilization rate. Accordingly, once appropriate indicators of the Turkish business cycle are selected, the question reduces to how the information coming from each variable will be aggregated to produce a robust measure of output gap immune to revision problems. While this study is the first one employing cyclical variables approach in estimating output gap for the Turkish economy, Rodriguez et. al. (2006) and Pybus (2011) can be documented as major pioneering works in the literature.

The main motivation of this study is the lack of an output gap measure for Turkey exempt from commonly-agreed pitfalls of filtering. Hence we aim at bringing about an improvement upon the existing studies in terms of revision properties and timeliness, which are crucial

[5] In the literature, the reliability of the alternative output gap estimates is widely discussed. Orphanides and van Norden (2002) summarize the factors that cause significant revisions on the output gap calculations in three branches. First, the revision may come from data revisions. Second, as new data on output for subsequent quarters become available, trends of the series may change. And finally, with the new data, the structure of the models that generate output gap estimates may be revised. See also Camba-Mendez and Rodriguez-Palenzuela (2003), Mitchell (2003) and Garratt et. al. (2008).

elements for a successful policy conduct in real-time.[6] In that sense, we introduce a completely different approach, based on selecting such variables that represent the cyclical state of the economy and extracting the common driver (factor) of them by employing a dynamic factor model. Then, this common factor is interpreted as an output gap indicator for Turkish economy. The estimated factor allows us to make historical assessments on the Turkish business cycles for the period of 2005-2013.

More importantly, regarding the time lags in the announcement of macroeconomic aggregates, i.e. GDP, we generate a significant improvement upon filtered measures as we produce timely information by making use of survey-based up-to-date variables. Hence, our approach brings about two noteworthy gains: First, backward revisions in our estimated measure of output gap are confined only to data updates since the uncertainty regarding trend estimation is out of question. Second, our measure gives cyclical information two-quarters in advance of any alternative filtered measure, i.e. Hodrick-Prescott (HP) filtered GDP.[7]

The paper proceeds as follows. In section 2, we explain the model and methodology in detail. Section 3 introduces the data set, where the choice of variables is a central issue for the study. In Section 4 we report empirical findings and interpret our estimated output gap indicator with special reference to the comparative analysis of past overheating episodes in Turkey. Section 5 concludes with general remarks and policy implications.

2. Methodology

In this paper we consider both small and large scale dynamic factor models. As is defined in Alvarez et. al. (2012), a model is called small scale dynamic factor model when the number of variables (N) is fixed and small and number of observations (T) is large. Small scale dynamic factor models (SSDFM) are mainly based on Stock and Watson (1991) single-index SSDFM. Mariano and Murasawa (2003), Nunes (2005), Aruoba et. al. (2009), Aruoba and Diebold (2010) and Camacho and Perez Quiros (2010) are some of the recent studies using SSDFM.

The other direction in the dynamic factor models is the large scale models (LSDFM) where both N and T are large. The roots of this approach are based on Stock and Watson (2002), which estimates the common component of many series using principal components estimator. LSDFMs are called approximate factor models and they lead to asymptotically consistent estimates when N and T tends to infinity. Some of the recent studies on this subject are Forni et. al. (2005), Giannone et. al. (2008) and Angelini et. al. (2011).

Dynamic factor models are generally used for forecasting purposes in the literature, where forecasting performance of small versus large scale dynamic factor models is widely discussed.[8] However, our focus in this paper is to extract the common component of selected

[6] Latest studies on estimating output gap for Turkey rely on statistical filters, with or without imposing a certain economic structure. See Öğünç and Ece (2004), Özbek and Özlale (2005), Kara et. al. (2005), Öğünç and Sarıkaya (2011), Alp et. al. (2012), Saygılı and Cihan (2008) and Üngör (2012).
[7] See Hodrick and Prescott (1997) for detailed information about the HP filter.
[8] See Boivin and Ng (2006), Bai and Ng (2008), Caggiano et. al. (2009), Banbura and Mondugno (2010), Banbura and Runstler (2011) and Alvarez et. al. (2012).

indicators of output gap rather than to forecast economic activity. Putting aside the principle of parsimony, it would be appropriate to use all available information, without any restrictions on the number of inputs, to produce an accurate and reasonable measure of output gap. Essentially we aim at deriving an up-to-date measure of output gap with good real-time properties by using natural indicators of the business cycle behavior. At the same time we also keep an eye on filtered measures of output gap to evaluate whether augmenting this information improve the reliability of our alternative measure. Hence we have two sets of indicators. One set consists of observable (unfiltered) business cycle indicators and the other one contains all indicators of output gap (filtered and unfiltered) in the data set. Since the first set covers only a few variables, we employ both SSDFM and LSDFM. However, the results of Phillips curve model estimations given in Section 3.1 point to use SSDFM. On the other hand, when using the bigger data set, the one that contains all the variables, encompassing information set does not allow us to use SSDFM and thus the associated factor is obtained through a LSDFM.

Regardless of the scale of the estimated model, the reasoning behind a dynamic factor model is that the dynamics of each series can be decomposed into two orthogonal components. The first component is called common component and it captures the collinear shocks that affect all the variables. The second component is called the idiosyncratic component and it captures the effect of those shocks affecting only that variable. The mathematical representation of this sentence may be as follows:

$$X_t = \chi_t + \xi_t = \gamma \times F_t + \xi_t, \tag{1}$$

where X_t denotes observed variables, χ_t is the common component and ξ_t denotes the idiosyncratic component, respectively. The common component, χ_t, can be decomposed into two parts; γ denotes matrix of factor loadings and F_t stands for vector of factors. In the literature it is generally assumed that the vectors F_t and ξ_t are serially and cross-sectionally uncorrelated unobserved stationary processes. The difference between a SSDFM and a LSDFM lies in their assumptions and variations in the estimation of the common component. A brief discussion of these two approaches is presented in the sections 2.1 and 2.2.

Once the factors are estimated, the question reduces to testing whether they are good indicators for the cyclical state of the economy. However, it is not straightforward to evaluate the reliability of the estimated factors with respect to a benchmark variable due to the unobserved nature of output gap. Hence, we make use of estimated Phillips curve equations and examine the statistical and economic significance of the factors in explaining inflation dynamics in Turkey.

Beside the role of estimated factors in a Phillips curve specification, we also check for their revision properties with respect to the arrival of new data. Undoubtedly, the common factor of unfiltered variables (natural indicators of business cycle) is expected to be superior to its filtered counterpart. Before going through the data in detail, we briefly present a technical review of dynamic factor models in the following section.

2.1. Small-scale dynamic factor model

In this study, we follow the technique proposed by Camacho and Perez Quiros (2010) which is based on Stock and Watson's (1991) single-index dynamic factor model. To give a dynamic structure to the model, an AR(2) process is assumed for common factor and for each of the idiosyncratic components. According to this approach, the state space representation of the model given in equation (1) consists of two equations. The first equation is the observation (measurement) equation and defined as follows:

$$\mathrm{X_t} = \mathrm{H} \times h_t + \mathrm{e_t}, \qquad \mathrm{e_t} \sim \mathrm{N}(0, \mathrm{R}) \tag{2}$$

In equation (2), $\mathrm{X_t}$ is the vector of observed variables, h_t is the vector that contains factor (common component) and idiosyncratic components, that is $h_t = (F_t', \xi_t')'$, and H is the matrix relating the common and idiosyncratic components to observables , that is $H = (\gamma\ I_N)$. In other words, H gives each indicator's loading on the common factor.

The second equation, transition equation, is stated as follows:

$$\mathrm{h_t} = \mathrm{M} \times \mathrm{h_{t-1}} + w_t, \qquad w_{\mathrm{t}} \sim \mathrm{N}(0, \mathrm{Q}) \tag{3}$$

where matrix M achieves the transition between states. The matrices M and Q are defined as follows:

$$M = \begin{pmatrix} \Phi & 0_{\mathrm{N}}' \\ 0_{\mathrm{N}} & \Theta \end{pmatrix} \tag{4}$$

$$Q = \begin{pmatrix} \Sigma_u & 0 \\ 0 & \Sigma_v \end{pmatrix} \tag{5}$$

where Φ and Θ are the autoregressive coefficients; Σ_u and Σ_v are the variances of the residual terms of the AR(2) models of common component and idiosyncratic components, respectively. The detailed state space form of the SSDFM estimated in this study is given in the Appendix.

Once the model is expressed in state space form, autoregressive parameters, vector of factor loadings and covariance matrix of idiosyncratic shocks are estimated by maximum likelihood using Kalman filter.

2.2. Large-scale dynamic factor model

The factor depending on the large data set is estimated through the LSDFM approach proposed by Banbura et. al. (2010). The estimated model is based on the model given in equation (1). Different from SSDFM, in this model there are more than one common factor which are assumed to be weakly correlated. In line with this assumption, the dynamics of the common factors are supposed to follow a VAR(1) process

$$F_t = \Theta F_{t-1} + u_t, \quad \mathrm{u_t} \sim \mathrm{N}(0, \mathrm{Q}) \tag{6}$$

where Θ is the matrix of autoregressive coefficients. In addition to this, the idiosyncratic components of the observable variables given in equation (1) are assumed to follow an AR(1) process. In this model, the parameters and the common factors are estimated using the quasi-maximum likelihood approach whose details can be found in Banbura et. al. (2010).

Considering approximate factor models, the choice of the number of dynamic factors emerges as a central issue and is widely discussed in the literature. To this aim, various approaches ranging from using empirical criteria to test statistics can be followed. For instance, some researchers choose to include those factors with an eigenvalue larger than unity (see Breitung and Eickmeier (2005)). On the other hand, Forni et. al. (2004), Bai and Ng (2002) and Onatski (2010) conduct several test procedures to decide on the numbers of factors to be used.[9] In this study, we used several approaches in the determination on the number of dynamic factors. In addition to the statistical test procedure of Onatski (2010), we constructed several output gap estimates with alternating number of dynamic factors. Then we investigated the performance of these output gap estimates in a Phillips curve framework given in section 3.1. The output gap estimate which gives the highest R^2 value is selected as our output gap measure.

3. Data

The methodology employed in this study is based on the use of cyclical indicators representing different branches of the economy. These indicators include both survey questions (soft data) regarding spare capacity, demand pressures, orders and recruitment difficulties along with widely used macroeconomic aggregates (hard data) such as national income, employment, unemployment rate, hours worked, real wages. Table 1 summarizes the data used in the analysis. Considering our primary focus that is, to produce an output gap measure free of statistical filters, we divide our data set in two categories. While the first set covers pure and observable indicators of business cycle, the remaining variables mostly include indicators of economic activity that were subject to a filtering procedure.

The analysis covers the period 2005Q1-2013Q1 at quarterly basis.[10] The series that exhibit a regular seasonal pattern are seasonally adjusted using Tramo/Seats technique. At first glance to the data list, the original frequencies of the variables seem to be mixed. For the monthly variables, all the transformations (seasonal adjustment and detrending) are conducted at monthly frequency, and then they are converted to quarterly frequency by taking three-months averages.[11] As a final adjustment, the series are standardized to avoid scale differences.[12]

[9] Forni et. al. (2004) suggests an informal criterion based on the portion of explained variances. Bai and Ng (2002) proposes selection procedures based on principal components. Onatski (2010) develops a new estimator based on selecting the eigenvalues which cluster around a single point.

[10] The beginning of our sample as 2005 is determined by the length of PMI indices and labor market data, i.e. employment and wages.

[11] In extracting the cycle component of the series, we use the standard HP filter.

[12] Standardization is done using the formula: $x_t^s = (x - \bar{x})/\sigma_x$. Here, x_t^s denotes the standardized series, $\bar{x}$ and σ_x denote mean and standard deviation of the series, respectively.

3.1. Selecting Variables

Recognizing the role of output gap in explaining inflationary pressures, it would be appropriate to introduce an economic criterion in the choice of variables. Thus we select those variables that have statistically significant explanatory power in a structural inflation equation. In doing so, we consider a generic, open economy Phillips curve equation:[13]

$$P_t = \alpha + \beta_0 \times P_{t-1} + \beta_1 \times PM_t + \gamma_i \times gap_{t-i} + e_t, \quad i = 0, 1, 2 \tag{7}$$

where P_t denotes quarterly consumer price inflation (CPI) excluding unprocessed food products, alcoholic beverages and tobacco products, PM_t denotes quarterly change in import unit value index (in Turkish Lira), gap_t represents the candidate series to be selected and e_t stands for the error term.[14] In this way, we define inflation inertia, import prices (including exchange rate pass-through) and output gap as major determinants of inflation in Turkey. We keep the variables representing inflation inertia and imported inflation as fixed and estimate equation (7) for each candidate "gap" indicator up to lag 2. Finally, output gap indicators, which are found to be statistically significant, are included in the dynamic factor models according to their lag structure.

4. Results

Selected indicators of output gap based on the estimated Phillips curve equations are presented in Table 2, where 20 out of 43 series are chosen as inputs to the common factor estimations. PMI indices, real effective exchange rate, financial conditions index, credits unit wage cost series for services are found to be statistically insignificant in explaining inflation developments. It is worth to note that data limitations on the services sector may be a hindrance against characterizing the broad picture of the economy, as we could use survey-based indicators only for the manufacturing sector. Given that unit wage cost and number of hours worked per employee for construction and services are found to be insignificant, factor estimates may largely reflect the trends in the manufacturing sector instead of the whole economy.

Table 3 illustrates Phillips curve estimation results for the series which are found to be statistically significant in equation (5). For the estimated coefficients to be comparable, we present them in standardized form. The lag structure, R^2 values and estimated coefficients tend to be close to each other. The estimated coefficients of output gap indicators vary

[13] Gali and Gertler (1999) estimate a closed economy version of the New-Keynesian Phillips curve under the assumption that price makers consist of both backward-looking and forward-looking units. Here we do not take into account a forward-looking Phillips curve; rather we construct a purely backward-looking one to capture the persistence in inflation process in Turkey as well as to simplify the analysis. Besides, we also include import prices denominated in Turkish lira to reflect the high degree of import price and exchange rate pass-through in Turkey. For empirical examination of import price and exchange rate pass-through in Turkey, see Leigh and Rossi (2002), Arbatli (2003), Kara and Öğünç (2008) and Yüncüler (2011).

[14] While unprocessed food prices are highly volatile and frequently exposed to supply side shocks, prices of alcoholic beverages and tobacco products are largely affected by fiscal adjustments in taxes. Hence we use a core inflation measure excluding volatile and administered items to better represent economic fundamentals. Consumer and import price inflation are defined as seasonally adjusted first differenced form of the corresponding price indices.

between 0.22 and 0.41, whereas import price pass-through is estimated to be between 0.39 and 0.57. Hence we can infer that imported inflation has a larger effect on pricing dynamics compared to the domestic factors.

For comparison purposes, we use HP filtered GDP series (HP_GDP_Gap hereafter) and treat it as an additional benchmark to check for the reliability of each output gap indicator along with the two final factor estimates. The last column of Table 3 reports the cross correlation between HP_GDP_Gap and each indicator. As expected, broad macroeconomic aggregates such as the components of GDP and labor market indicators have the highest correlation with HP_GDP_Gap.

The last three rows of Table 3 present the estimation results for the three measures of output gap. In statistical terms, we cannot distinguish between these three measures neither with the R^2 values nor the magnitude of estimated coefficients. At first glance, two indicators that were constructed with filtered variables move very closely and display the same pattern in terms of the timing of turning points (Figure 1). However, what really matters for a policymaker and thus our primary focus is the reliability of the factor depending on purely observable output gap indicators. Compared to the filter-based measures, it demonstrates a similar tendency throughout the sample and well tracks the turning points of the business cycle, albeit with a smaller variation around mean. Besides, historical illustration of past decade is also consistent with the results of recent studies on the Turkish economy. Hence, even when we employ only survey-based soft data without any resort to a broad measure of economic activity such as GDP and unemployment, we could be able to produce an economically meaningful indicator of output gap for the Turkish economy.

One common message from the output gap measures in Figure 1 is that the period of 2005-2008 points to overheating in the Turkish economy. Output gap estimates averaged between 1.9-2.8 percent during this episode, while the estimated peaks of alternative measures range from 3.5 to 5 percent. This overexpansion phase was followed by the notorious global crisis dragging the economy into a deep recession at the end of 2008. The rapid collapse in economic activity for two successive quarters resulted in a deep trough in the first quarter of 2009 and below-potential levels of output prevailed for almost two years. Economic activity could only reach at its natural level in late-2010. For all three measures indicate an above-potential level of economic activity for 2011, where observable gap indicator does not give a significant overheating signal unlike filtered measures. Since then, economic activity has been displaying a gradual slowdown and output returned back to below-potential levels as of the beginning of 2013, as confirmed by all measures.

4.1. Revision Properties

Since output gap is unobservable, the absence of a "true" benchmark makes it difficult to assess the quality of any estimate. The uncertainty surrounding the estimates leads policymakers to assess the reliability of an output gap measure with respect to its revision properties. Hence we mainly aim at deriving a business cycle indicator solely from directly observable indicators of output gap, while avoiding the revision uncertainty as much as possible. In this respect, the revision performance of Observable_Gap is compared with that of HP_GDP_Gap.

We introduce six vintages for the two gap measures in question. The first vintage is defined for 1998Q1-2007Q4, while the end-point is recursively extended at a 4-quarters basis. Here, the first five vintages represent the real-time estimates and the last vintage, namely 1998Q1-2012Q4, provides the final estimate. Seasonal adjustment and detrending procedures are repeated for each vintage using only the available data. Since the series that constitute Observable_Gap are not revised and are not detrended in any way, revisions are confined to the re-estimation of seasonal adjustment model and dynamic factor model.

On the contrary, the revisions observed in HP_GDP_Gap come from different sources. First, at each official release, the last two years' observations of GDP are revised. Moreover, seasonal component of GDP and trend estimates also change with new information. Since the source of revisions −whether emanating from the decomposition of components (seasonal adjustment and detrending) or from official changes in the data− is hard to distinguish, we concentrate on the total revision, defined as the difference between real-time and final estimates.

Figure 2 shows the real-time and final estimates of Observable_Gap series. It is clear that there is no significant difference between the factor estimates for alternative vintages. However, HP_ GDP_GAP estimates presented in Figure 3 largely depend on the sample and the most striking example seems to be the year 2007. While the real-time estimate calls for an expansionary policy conduct for the second half of 2007, successive estimates for the same period point to a significant degree of overheating, which requires a policy tightening. The real-time performance of Observable_Gap regarding the same period is impressive, as it successfully delivers the correct signal for policy implementation.

Figure 4 and Figure 5 allows us to make a visual evaluation of revisions in the estimated factors. The revisions in HP_ GDP_Gap are extremely high, where they reach up to 6 percentage points in absolute values. Undoubtedly, real-time policy practice cannot tolerate such a huge revision in output gap estimates. On the other hand, the revisions in Observable_Gap estimates are close to zero, except for 2007, where the largest revision stands at 2 percentage points.

Following Orphanides and van Norden (2002), we complement the graphical illustration by providing several descriptive statistics for the total revisions. Table 5 presents the mean, standard deviation, root mean square (RMS), minimum value (Min), maximum value (Max) and first-order serial correlation (AR) of the total revision series.[15] For each statistical criterion, Observable_Gap proves to be superior to HP_ GDP_Gap in terms of revisions. Besides having a greater mean, standard deviation and root mean square, total revisions in HP_ GDP_GAP prove to be more persistent than those in Observable _Gap.

[15] In calculating the averages, we exclude the vintage ending at 2009Q4 due to the distortionary effect of global financial crises on the variables.

Table 6 provides some reliability measures of the significance of the revisions relative to the final estimates for each output gap measure. COR denotes the correlation of the real-time and final estimates, NS (NSR) indicates the ratio of the standard deviations (the root mean squares) of total revisions and final estimates of the output gap. NSR represents the effect of persistent upward or downward revisions. These statistics also support the superiority of Observable_Gap as having relatively closer real-time and final estimates as well as less persistent revisions. Finally, OPSIGN, which shows the ratio of real-time and final gap estimates that have opposite signs to total number of observations, indicates that real-time estimates frequently correctly classify the sign of the gap without any major difference between the two measures.

All in all, both visual and statistical examination of the two alternative measures of output gap shows that the one incorporating only unfiltered data has better real-time properties compared to the benchmark HP-filtered GDP cycle. Making time series decomposition out of question by using direct indicators of business cycle minimizes the revision problem of conventional methods of estimating output gap. We show that revision uncertainty in output gap estimates can be overcome by employing soft and unfiltered data, characterizing the cyclical position, not the level, of economic activity.

5. Concluding Remarks

We produced a reliable indicator of output gap for the Turkish economy, even without making use of broad measures of economic activity, i.e. GDP and unemployment rate, and any kind of filters. Our approach has two main pillars: First, we choose such variables that directly represent the cyclical state of the Turkish economy. Capacity utilization rate is a good example for those variables in our radar, since it contains information on the cycle, not the level, of economic activity. We selected five additional variables including the change in purchasing power, the level of orders compared to their normal, the adequacy of production capacity with respect to orders and expected demand, the views of manufacturing firms on demand conditions and the number of applications per new job announcement. As the second step, we model business cycle as the common driver of the selected variables and estimate it in a small scale dynamic factor model setting.

For comparison purposes we also augmented HP-filtered data with natural indicators of business cycle mentioned above and estimate the common component in a large scale dynamic factor model. The factors not only proved to be statistically significant in estimated Phillips equations, but also provided economically meaningful information for historical accounting of Turkish business cycles. More importantly, our filter-free output gap indicator is superior to any other filter-based measure as being immune to revisions with respect to the arrival of new information. Aggregating representative and direct indicators of business cycle in a statistically optimal manner proved to be successful in coping with revision uncertainty embodied in statistical filters.

Besides, the use of up-to-date survey-based variables instead of filtered macroeconomic aggregates minimized the problem of lagging data. In this way, the most remarkable improvement over conventional measures of output gap has been the success in generating timely information, as we provided information on the cyclical position of the economy two-quarters in advance of the GDP. Hence, it is not only the immunity to revisions but also the timeliness property made our filter-free output gap indicator a robust tool for real-time policymaking.

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Table 1: Data Set

Acronym	Observable Output Gap Indicators	Frequency	Source
s1	PMI_Backlogs of work	Monthly	MARKIT
s2	Purchasing power (present compared to past six months)	Monthly	CBRT
s3	Office market vacancy rate (inverted)	Quarterly	PROPIN
s4	BTS_Considering your current order books and the expected change in demand over the coming months, how do you assess your current production capacity? (not sufficient-more than sufficient, percentage)	Monthly	CBRT
s5	BTS_What main factors are currently limiting your production? (percentage of answering insufficient demand)(inverted)	Monthly	CBRT
s6	BTS_Amount of current overall order books (above normal-below normal, percentage)	Monthly	CBRT
s7	Number of applications per new job announcement (inverted)	Monthly	Kariyer.net
s8	Capacity utilization rate (percentage)	Monthly	CBRT
s9	Number of hours worked per employee (total industry)	Quarterly	TURKSTAT
s10	Number of hours worked per employee (manufacturing industry)	Quarterly	TURKSTAT
	Series Related With Economic Activity		
s11	PMI_Total Index	Monthly	MARKIT
s12	PMI_New orders/Stocks	Monthly	MARKIT
s13	PMI_New orders	Monthly	MARKIT
s14	PMI_New export orders	Monthly	MARKIT
s15	PMI_Output	Monthly	MARKIT
s16	PMI_Suppliers' Delivery Times (inverted)	Monthly	MARKIT
s17	PMI_Employment	Monthly	MARKIT
s18	BTS_How have your overall orders developed over the past 3 months? (increased-decreased, percentage)	Monthly	CBRT
s19	BTS_How has your production developed over the past 3 months? (increased-decreased, percentage)	Monthly	CBRT
s20	BTS_How do you expect your firm's total employment to change over the next 3 months? (increased-decreased, percentage)	Monthly	CBRT
s21	Energy gap	Monthly	TEIAS
s22	Services sector value added gap	Quarterly	TURKSTAT
s23	Net foreign demand gap (inverted)	Quarterly	TURKSTAT
s24	Total industry value added gap	Quarterly	TURKSTAT
s25	Domestic demand gap	Quarterly	TURKSTAT
s26	Industrial production gap	Monthly	TURKSTAT
s27	Foreign sales gap	Monthly	TURKSTAT
s28	Domestic sales gap	Monthly	TURKSTAT
s29	Non-farm unemployment rate gap (inverted)	Monthly	TURKSTAT
s30	Non-farm employment gap	Monthly	TURKSTAT
s31	Number of new job announcements gap	Monthly	Kariyer.net
s32	The number of newly established companies gap	Monthly	TOBB
s33	Financial conditions index	Monthly	CBRT
s34	The difference between the annual growth of total nominal domestic credit and nominal GDP	Quarterly	CBRT, TURKSTAT
s35	Domestic outstanding credit gap (real)	Monthly	CBRT
s36	Gap of unit labor cost based real effective exchange rate	Quarterly	CBRT

s37	Gap of CPI based real effective exchange rate	Monthly	CBRT
s38	Gap of real unit wage cost (industry sector)	Quarterly	TURKSTAT
s39	Gap of real unit wage cost (construction sector)	Quarterly	TURKSTAT
s40	Gap of real unit wage cost (wholesale and retail trade and services sector)	Quarterly	TURKSTAT
s41	OECD region output gap	Quarterly	OECD
s42	Global PMI_Manufacturing and Services Composite Index	Monthly	MARKIT
s43	Global PMI_Backlogs of work	Monthly	MARKIT

Notes:

s1: PMI_backlogs of work index gives an indication of arrears of new orders a firm needs to overtake given to a capacity level. The index varies according to the amount of new orders received by the firm. Since an increase in the index shows an increase in the demand compared to a given capacity, this series is considered as an indicator of output gap.

s2: An increase in the purchasing power across time can be considered as an indicator of demand pressures in the economy. Besides, if the increase in the purchasing power stems from an increase in the wages it may also signal cost-push inflationary pressures.

s3: Office vacancy rate is the ratio between total vacant areas and total office areas in İstanbul office market and it is compiled from the reports of Property Investment Consultancy (PROPIN). A decrease in the vacancy rate may be an indication of the economic vitality. To make it procyclical with the output gap, inverted version is used in the analysis.

s4: Adequacy of production capacity with respect to current and expected demand can be deemed as a direct indicator of output gap, as it contains information on the capacity pressures (ability of the sector to meet demand with existing capacity).

s7: Number of applications per new job announcement can be considered a measure of the slack in the labor market. Besides, it moves very close with the non-farm unemployment rate. During recovery (slowdown) episodes number of applications per new job announcement is expected to decrease (increase). The series is inverted for the sake of compatibility.

s9-s10: Number of hours worked per employee is highly responsive to economic fluctuations. Working hours can be interpreted as the labor utilization rate and can be adjusted in accordance with the phase of the business cycle.

s33: Financial conditions index (FCI) is constructed by using the cyclical components of indicative bond interest rate and weighted average interest rates for cash, vehicle, housing and commercial loans employing small scale dynamic factor model. Since FCI is a leading indicator of economic activity, the lag order is taken into account in the analysis.

s36-s37: The increase in the real effective exchange rate shows the appreciation of the Turkish Lira (TL). As being the quickest channel of monetary transmission, the deviation of real exchange rate from its long-run trend is included in the analysis.

s38-s39-s40: For the Turkish economy, the cyclical components of real unit wages are highly correlated and move in the same direction with the output gap series. An above-trend level of real unit wages (real marginal costs) can be considered to be a source of cost-push inflation.

Table 2: Included and Excluded Series

Included Series
Observable Gap Indicators
Purchasing power (present compared to past six months)
BTS_Considering your current order books and the expected change in demand over the coming months, how do you assess your current production capacity? (not sufficient-more than sufficient, percentage)
BTS_What main factors are currently limiting your production? (percentage of answering insufficient demand)(inverted)
BTS_Amount of current overall order books (above normal-below normal, percentage)
Number of applications per new job announcement (inverted)
Capacity utilization rate (percentage)
Series Related With Economic Activity
BTS_How have your overall orders developed over the past 3 months? (increased-decreased, percentage)
BTS_How has your production developed over the past 3 months? (increased-decreased, percentage)
BTS_How do you expect your firm's total employment to change over the next 3 months? (increased-decreased, percentage)
Energy gap
Services sector value added gap
Total industry value added gap
Domestic demand gap
Industrial production gap
Non-farm unemployment rate gap (inverted)
Non-farm employment gap
Number of new job announcements gap
Gap of real unit wage cost (industry sector)
OECD region output gap
Gap of number of hours worked per employee (total industry)
Excluded Series
Observable Gap Indicators
PMI_Backlogs of work
Office market vacancy rate (inverted)
Series Related With Economic Activity
PMI_Total Index
PMI_New orders/Stocks
PMI_New orders
PMI_New export orders
PMI_Output
PMI_Suppliers' Delivery Times (inverted)
PMI_Employment
Net foreign demand gap (inverted)
Foreign sales gap
Domestic sales gap
The number of newly established companies gap
Financial conditions index
The difference between the annual growth of total nominal domestic credit and nominal GDP
Domestic outstanding credit gap (real)

Gap of unit labor cost based real effective exchange rate
Gap of CPI based real effective exchange rate
Gap of number of hours worked per employee (manufacturing industry)
Gap of real unit wage cost (construction sector)
Gap of real unit wage cost (wholesale and retail trade and services sector)
Global PMI_Manufacturing and Services Composite Index
Global PMI_Backlogs of work

Table 3: Phillips Curve Estimation Results

Series	Lag order	R-square	Standardized Coefficients: Series[1]	P(-1)[2]	Pm[3]	Cross-correlation with HP_GDP_Gap: Lag order	Value
Purchasing power	-2	0.634	0.249	0.338	0.543	-1	0.690
BTS_Level of current production capacity compared to expected demand	-1	0.686	0.352	0.330	0.486	-1	0.624
Capacity utilization rate	0	0.646	0.299	0.323	0.518	0	0.851
BTS_Factors that limit production (insufficient demand)(inverted)	0	0.661	0.322	0.334	0.503	0	0.918
BTS_Amount of current overall order books	0	0.627	0.239	0.115	0.512	0	0.866
Number of applications per new job announcement (inverted)	0	0.624	0.254	0.341	0.508	+1	0.887
BTS_Change in overall orders over the past 3 months	0	0.632	0.244	0.113	0.519	-1	0.787
BTS_Change in production over the past 3 months?	0	0.628	0.238	0.114	0.513	-1	0.763
BTS_Change in firm's total employment over the next 3 months	0	0.628	0.231	0.444	0.545	-1	0.848
Energy gap	-1	0.634	0.272	0.137	0.567	0	0.769
Services sector value added gap	0	0.689	0.336	0.372	0.473	0	0.947
Total industry value added gap	0	0.676	0.311	0.380	0.482	0	0.963
Domestic demand gap	-1	0.634	0.287	0.297	0.472	0	0.862
Gap of number of hours worked per employee	0	0.716	0.355	0.431	0.503	0	0.652
Non-farm unemployment rate gap (inverted)	0	0.637	0.331	0.280	0.443	0	0.919
Non-farm employment gap	0	0.615	0.271	0.305	0.464	+1	0.841
Industrial production gap	0	0.651	0.311	0.369	0.457	0	0.914
OECD region output gap	0	0.616	0.216	0.366	0.561	0	0.596
Number of new job announcements gap	0	0.625	0.253	0.364	0.490	0	0.958
Gap of real unit wage cost	0	0.706	0.406	0.341	0.387	0	0.850
OG_observable gap indicators[4]	0	0.665	0.334	0.283	0.499	0	0.946
OG_all series[5]	0	0.661	0.321	0.330	0.468	0	0.974
HP_GDP_Gap	0	0.686	0.331	0.342	0.462	-	-

Notes:
1) shows the estimated coefficient of each output gap indicator.
2) shows the estimated coefficient of lag of dependent variable.
3) shows the estimated coefficient of import price index.
4) denotes the calculated output gap using only six observable output gap indicator.
5) denotes the calculated output gap using all the output gap indicators.

Table 4: Factor Loadings

Output Gap (observable gap indicators)	
Purchasing power	12.4
BTS_Level of current production capacity compared to expected demand	12.6
BTS_Factors that limit production (insufficient demand)(inverted)	20.0
BTS_Amount of current overall order books	16.9
Number of applications per new job announcement (inverted)	19.4
Capacity utilization rate	18.8
Output Gap (all series)	
Purchasing power	4.2
BTS_Level of current production capacity compared to expected demand	3.9
BTS_Factors that limit production (insufficient demand)(inverted)	5.5
BTS_Amount of current overall order books	5.6
Number of applications per new job announcement (inverted)	5.1
Capacity utilization rate	5.5
BTS_Change in overall orders over the past 3 months	4.6
BTS_Change in production over the past 3 months?	4.5
BTS_Change in firm's total employment over the next 3 months	4.9
Energy gap	4.6
Services sector value added gap	5.8
Total industry value added gap	5.9
Domestic demand gap	5.5
Gap of number of hours worked per employee	3.9
Non-farm unemployment rate gap (inverted)	5.4
Non-farm employment gap	4.9
Industrial production gap	5.6
OECD region output gap	3.9
Number of new job announcements gap	5.7
Gap of real unit wage cost	5.0

Table 5: Summary Revision Statistics

Method	Mean	Standard Deviation	RMS	Min	Max	AR
Observable_Gap	-0.058	0.313	0.343	-0.853	0.568	0.681
HP_GDP_Gap	-0.197	0.936	0.981	-2.769	1.318	0.801

Note:
For each output gap measure, the statistics in the table are calculated using the total revision series given in Figure 4 and Figure 5. Then, their averages are presented in Table 5.

Table 6: Summary Reliability Indicators

Method	COR	NS	NSR	OPSIGN(%)
Observable _Gap	0.980	0.167	0.183	5.94
HP_GDP_Gap	0.946	0.253	0.265	4.93

Note:
For each output gap measure, the statistics in the table are calculated using the total revision series given in Figure 4 and Figure 5. Then, their averages are presented in Table 6.

Figure 1: Estimated Output Gap Series

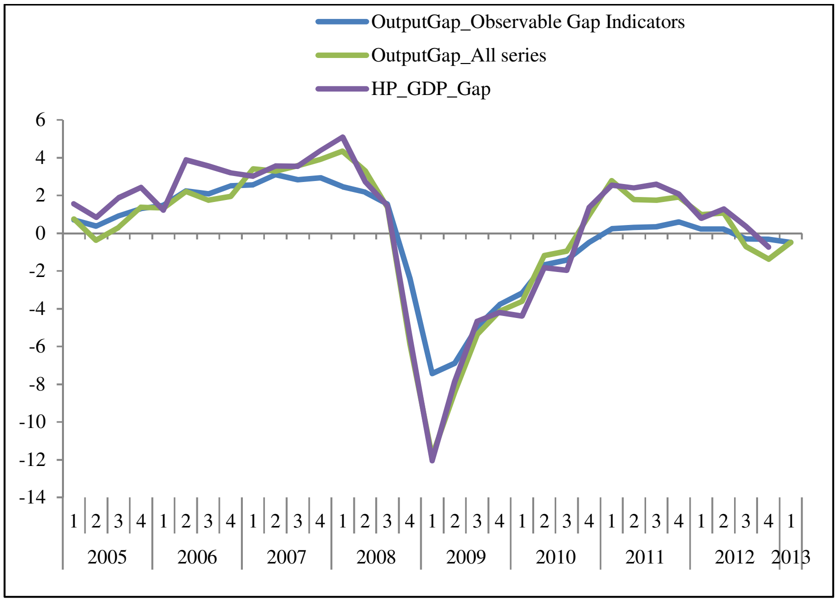
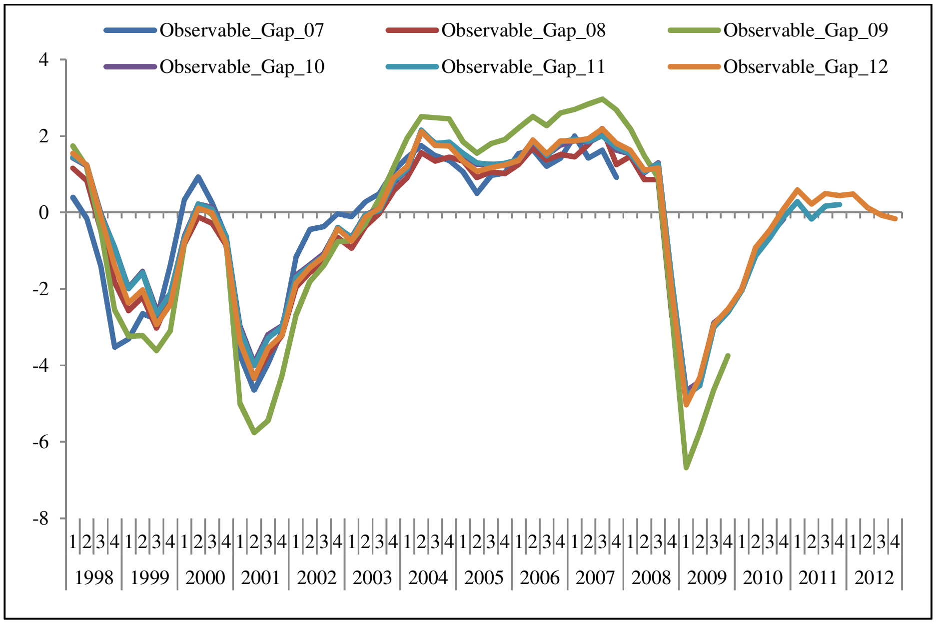
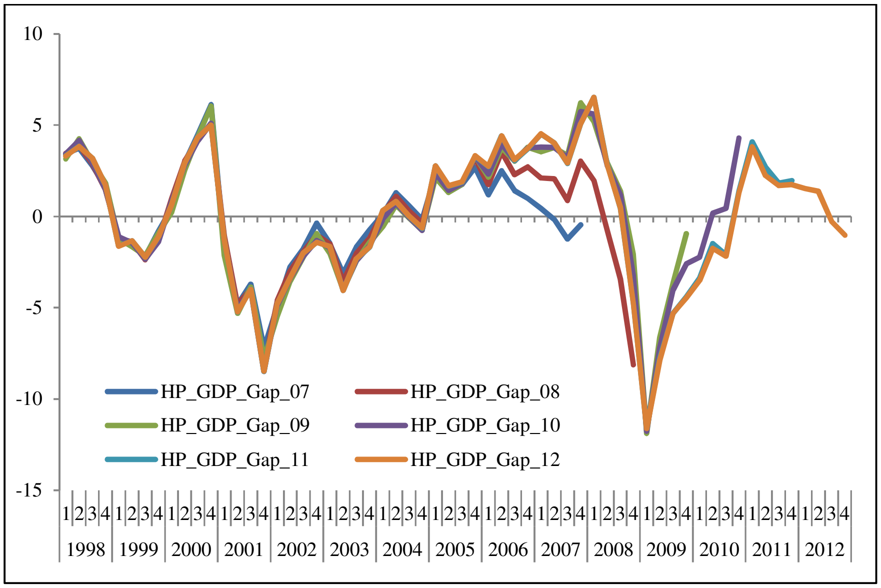


Figure 2: Output Gap (with Observable Gap Indicators) by Several Vintages



Note:
Observable_Gap_07,…, Observable _Gap_11 are the real-time estimates and Observable _Gap_12 is the final estimate.

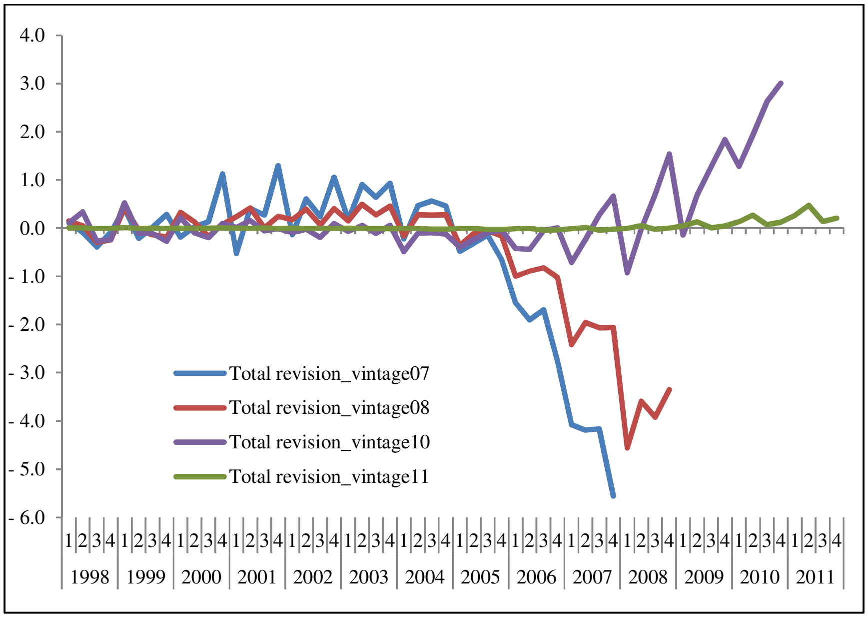
Figure 3: Output Gap (with HP Filter) Estimates by Several Vintages



Note:
HP_GDP_Gap_07,…, HP_GDP_Gap _11 are the real-time estimates and HP_GDP_Gap_12 is the final estimate.

Figure 4: Revisions in Output Gap (with Observable Gap Indicators)

Figure 5: Revisions in Output Gap (with HP Filter)



Appendix: The small scale dynamic factor model used in the paper

This section gives the SSDFM used in this paper. The model contains six observable variables. In the equations x_{it} denote observed series; γ_i's are factor loadings; f_t is common factor and ξ_{it}'s are idiosyncratic components.

The open form of the measurement equation is as follows:

$$\begin{aligned} x_{1t} &= \gamma_1 f_t + \xi_{1t} + e_{1t} \\ x_{2t} &= \gamma_2 f_t + \xi_{2t} + e_{2t} \\ x_{3t} &= \gamma_3 f_t + \xi_{3t} + e_{3t} \\ x_{4t} &= \gamma_4 f_t + \xi_{4t} + e_{4t} \\ x_{5t} &= \gamma_5 f_t + \xi_{5t} + e_{5t} \\ x_{6t} &= \gamma_6 f_t + \xi_{6t} + e_{6t} \end{aligned}$$

The matrix representation of the measurement equation is as follows:

$$\underbrace{\begin{bmatrix} x_{1t} \\ x_{2t} \\ x_{3t} \\ x_{4t} \\ x_{5t} \\ x_{6t} \end{bmatrix}}_{X_t} = \underbrace{\begin{bmatrix} \gamma_1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ \gamma_2 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ \gamma_3 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ \gamma_4 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ \gamma_5 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ \gamma_6 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \end{bmatrix}}_{H} \times \underbrace{\begin{bmatrix} f_t \\ f_{t-1} \\ \xi_{1t} \\ \xi_{1t-1} \\ \xi_{2t} \\ \xi_{2t-1} \\ \xi_{3t} \\ \xi_{3t-1} \\ \xi_{4t} \\ \xi_{4t-1} \\ \xi_{5t} \\ \xi_{5t-1} \\ \xi_{6t} \\ \xi_{6t-1} \end{bmatrix}}_{h_t} + \underbrace{\begin{bmatrix} e_{1t} \\ e_{2t} \\ e_{3t} \\ e_{4t} \\ e_{5t} \\ e_{6t} \end{bmatrix}}_{e_t}$$

We assume that common factor and the idiosyncratic components follow an AR(2) process. So, the transition equation has the following open form:

$$\begin{aligned} f_t &= \varphi_1 f_{t-1} + \varphi_2 f_{t-2} + u_{1t} \\ f_{t-1} &= f_{t-1} \\ \xi_{1,t} &= \theta_1 \xi_{1,t-1} + \theta_2 \xi_{1,t-2} + v_{1t} \\ \xi_{1,t-1} &= \xi_{1,t-1} \\ \xi_{2,t} &= \theta_3 \xi_{2,t-1} + \theta_4 \xi_{2,t-2} + v_{2t} \\ \xi_{2,t-1} &= \xi_{2,t-1} \\ \xi_{3,t} &= \theta_5 \xi_{3,t-1} + \theta_6 \xi_{3,t-2} + v_{3t} \\ \xi_{3,t-1} &= \xi_{3,t-1} \\ \xi_{4,t} &= \theta_7 \xi_{4,t-1} + \theta_8 \xi_{4,t-2} + v_{4t} \\ \xi_{4,t-1} &= \xi_{4,t-1} \\ \xi_{5,t} &= \theta_9 \xi_{5,t-1} + \theta_{10} \xi_{5,t-2} + v_{5t} \\ \xi_{5,t-1} &= \xi_{5,t-1} \end{aligned}$$

$$\xi_{6,t} = \theta_{11}\xi_{6,t-1} + \theta_{12}\xi_{6,t-2} + v_{6t}$$
$$\xi_{6,t-1} = \xi_{6,t-1}$$

The matrix representation of the transition equation is as follows:

$$\underbrace{\begin{bmatrix} f_t \\ f_{t-1} \\ \xi_{1,t} \\ \xi_{1,t-1} \\ \xi_{2,t} \\ \xi_{2,t-1} \\ \xi_{3,t} \\ \xi_{3,t-1} \\ \xi_{4,t} \\ \xi_{4,t-1} \\ \xi_{5,t} \\ \xi_{5,t-1} \\ \xi_{6,t} \\ \xi_{6,t-1} \end{bmatrix}}_{h_t} = \underbrace{\begin{bmatrix} \varphi_1 & \varphi_2 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & \theta_1 & \theta_2 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \theta_3 & \theta_4 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & \theta_5 & \theta_6 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \theta_7 & \theta_8 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \theta_9 & \theta_{10} & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \theta_{11} & \theta_{12} \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \end{bmatrix}}_{M} \times \underbrace{\begin{bmatrix} f_{t-1} \\ f_{t-2} \\ \xi_{1,t-1} \\ \xi_{1,t-2} \\ \xi_{2,t-1} \\ \xi_{2,t-2} \\ \xi_{3,t-1} \\ \xi_{3,t-2} \\ \xi_{4,t-1} \\ \xi_{4,t-2} \\ \xi_{5,t-1} \\ \xi_{5,t-2} \\ \xi_{6,t-1} \\ \xi_{6,t-2} \end{bmatrix}}_{h_{t-1}} + \underbrace{\begin{bmatrix} u_t \\ 0 \\ v_{1,t} \\ 0 \\ v_{2,t} \\ 0 \\ v_{3,t} \\ 0 \\ v_{4,t} \\ 0 \\ v_{5,t} \\ 0 \\ v_{6,t} \\ 0 \end{bmatrix}}_{w_t}$$

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