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Nowcasting Turkish GDP with MIDAS: Role of Functional Form of the Lag Polynomial

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NOWCASTING TURKISH GDP WITH MIDAS: ROLE OF FUNCTIONAL FORM OF THE LAG POLYNOMIAL

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ABSTRACT

In this paper, we analyze short-term forecasts of Turkish GDP growth using Mixed DAta Sampling (MIDAS) approach. We consider six alternatives for functional form of the lag polynomial in the MIDAS equation, five to twelve lags of the explanatory high frequency variables and produce short-term forecasts for nine forecast horizons starting with the release of data for six months before the start of the target quarter to the release of the data for the last month of the quarter. Our results indicate that functional form of the lag polynomials play non-negligible role on the short-term forecast performance but a specific functional form does not perform globally well for all forecast horizons, for all lag lengths or for all indicators. Import quantity indices perform relatively better until first month's data for the target quarter become available. As data accumulate for the monthly indicators for the target quarter, real domestic turnover and industrial production indicators stand out in terms of short-term forecasting performance. When all of the three months' realizations for the monthly indicators become available for the quarter that we want to forecast, unrestricted MIDAS type equations with around five lags with real domestic turnover and industrial production indicators track the GDP growth relatively successfully.

ÖZET

Bu çalışmada, MIDAS yaklaşımı ile kısa dönemli GSYİH büyümesi tahminleri incelenmektedir. MIDAS denklemi kapsamında, açıklayıcı değişkenlerin beşten on ikiye kadar gecikmeli değerleri kullanılmış, bu gecikmeli değerlerinin katsayılarının modellenmesi için altı farklı fonksiyonel form değerlendirilmeye alınarak tahmin edilmek istenilen çeyrekten altı ay öncesine ilişkin verilerin açıklaması ile çeyreğe ilişkin tüm verilerin tamamlanmasına kadar geçen süreç için dokuz ayrı tahmin üretilmiştir. Gecikmeli değerler için tanımlanan fonksiyonel form kısa dönemli tahmin performansında önemli rol oynayabilmektedir. Ancak, tüm tahmin ufukları, gecikme değerleri ve değişkenler için belirli bir fonksiyonel form en iyi sonucu vermemektedir. Sonuçlar, tahmin edilmek istenilen çeyreğe ilişkin ilk veriler açıklanana kadar ithalat miktar endeksinin görece daha iyi tahminler ürettiğine işaret etmektedir. Çeyreğe ilişkin veriler biriktikçe, sanayi sektöründeki reel cirolar ile sanayi üretim endeksi göstergeleri tahmin performansı açısından öne çıkmaktadır. Bir çeyreğe ilişkin tüm veriler tamamlandığında ise beş gecikme kullanan kısıtlanmamış MIDAS tipi bir denklem ile sanayi sektöründeki reel cirolar ile sanayi üretim endeksi ile üretilen tahminler GSYİH büyümesine oldukça yakın bir hareket sergilemektedir.

JEL classification: C53; E37

Keywords: GDP forecasting; MIDAS; polynomial form.

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Non-technical Summary

Forecasting key macroeconomic variables such as inflation, unemployment and GDP growth is an integral part of the real-time policy making process. These indicators have their own peculiar characteristics that should be taken into account in the forecasting process to obtain timely, accurate and robust forecasts. There are two issues that have to be taken care of for short-term GDP forecasts: mixed frequency and publication lags. GDP data are available at the quarterly frequency while indicators like industrial production and surveys are available on a monthly basis. This type of a data set, which is composed of quarterly and monthly indicators, is dubbed as mixed-frequency. Second issue is about publication lags. GDP data for a given quarter are published around two months after the end of the quarter while monthly indicators become available on a more timelier basis but, for hard data such as industrial production, with a certain lag as well. Therefore, depending on the timing of the forecasts, there may be missing data for the monthly indicators too. One of the methods that can deal with mixed frequency issue and publication lags is MIDAS approach that enables one to use monthly indicators for forecasting GDP growth.

In this paper, we analyze the short-term forecasting performance of MIDAS approach for various indicators such as industrial production, trade indices, taxes, sales and credit. We analyze a total of thirty indicators. Specifying a MIDAS equation requires choices about the lag length of the monthly indicators and the functional form for modelling those lags. We analyze effect of these specifications by using eight different lags and six functional forms. Forecasts are produced starting with the release of data for the six months before the start of the quarter to the release of the all of the three months' data for the quarter by taking into account what would a forecaster observe at the time of forecasting.

Our results indicate that functional form of the lag polynomial plays non-negligible role on the short-term forecast performance but a specific functional form does not perform globally well for all forecast horizons or for all indicators. Lag length structure of the high frequency indicator also affects the results. Our results indicate that before any realization is observed for monthly data for the target quarter, import quantity indices performs relatively well. Once data start to accumulate for the quarter that we want to forecast, real domestic turnover and industrial production indicators provides the best forecasts. Visual inspection of the short-term forecasts of the best performing specifications show that they can track the developments in GDP quite successfully.

1. INTRODUCTION

In this paper we analyze forecast performance of Mixed DAta Sampling (MIDAS) approach for short-term forecasts of Gross Domestic Product (GDP) growth for Turkish economy for the period of 2014Q2-2019Q1. Our results indicate that modelling specifications in the MIDAS approach, in terms of the combination of functional form of the lag polynomial and the lag length, affect the forecast performance but there is not a unique specification that performs best for all indicators and for all forecast horizons. Depending on the forecast horizon, different indicators stand out in terms of forecast performance as well. So, while MIDAS approach can effectively deal with mixed frequency and publication lag issues, it is important to analyze the sensitivity of the forecast performance to the modelling choices before using MIDAS type equations for forecasting Turkish GDP growth.

GDP provides a comprehensive view about the state of economic activity. Hence, developments in the GDP growth are closely monitored by policy makers and market participants. Yet, GDP data are available at quarterly frequency with a publication lag that can range from 30 to 60 days, and in some cases longer, depending on the country. This means that decision makers that use GDP growth as an input will not be able to utilize the GDP data for the quarter in which they are making decision. Indeed, nowcasting is coined as a term to reflect the fact that forecasts of GDP series should be produced in the reference quarter due to publication lags (Banbura et al. ,2012).

Several methods have been developed for producing early predictions of GDP growth. A branch of the forecasting literature concentrates on developing techniques to utilize information content of high frequency indicators such as monthly industrial production or weekly credit data in real time. Two issues that have to be resolved for this aim is to deal with the so-called ragged end issue at the end of the sample stemming from missing data for the high frequency indicators due to publication lags and mixed frequency nature of the data. In order to put the discussion in a more concrete set up, consider the case that industrial production data for February are published in April. Since March figure for industrial production would be missing in April, updating the forecast for the first quarter's GDP after the announcement of February industrial production would require handling incomplete data for the target quarter, i.e. the quarter that we want to forecast. A reading of the literature shows that initially bridge equation approach was used to utilize mixed-frequency data for short-term forecasts of GDP growth. In this approach, in order to address the issue of publication lags, missing monthly data are forecast using auxiliary models, such as simple AR models. Then these monthly indicators are converted to quarterly frequency and OLS regressions are used to estimate coefficients and obtain forecasts (Baffigi et al. (2004) and Diron (2008)). In the given example, March industrial production growth can be forecast with an AR model, then quarterly average of the industrial production can be obtained by combining realizations for January and February with forecast of March. This quarterly growth for industrial production can be used to update the forecast for the first quarter's GDP growth.

In a seminal paper, Giannone et al. (2008) show that it is possible to estimate factors for a mixed frequency data set using Kalman filter after expressing the system in the state-space form. Their findings show that as data accumulates for a given quarter, nowcast errors decline. Several studies tested the performance of factor models for various countries and found promising results for nowcasting with factor models. Over time, in addition to bridge equations, factor models became a popular tool for forecasting teams.

In the meantime, Ghysels et al. (2004) developed another method for utilizing mixed frequency data for modelling financial variables. They call this approach as MIDAS. In a nutshell, instead of averaging the higher frequency variable to match the frequency of low frequency variable, as in the case of bridge equations, one regresses low frequency variable onto higher frequency variable. For instance, Ghysels et al. (2006) estimate weekly volatility using daily returns. They use up to 50 lags of the daily indicators. Clements and Galvao (2008 and 2009) conjectured that while MIDAS approach is in general used for financial applications, it is indeed well suited to the task of nowcasting GDP growth. They use several monthly indicators for nowcasting quarterly US GDP growth. Subsequent studies analyzed the performance of MIDAS approach for different countries and it is now included in the toolkit of short-term forecasts of some central banks.

A defining characteristic of MIDAS approach compared to other techniques that can deal with unbalanced data sets is that forecast equations are set up in the spirit of direct forecasting rather than forecasting missing values of the higher frequency indicators (see for example Schumacher (2016)). Innovation in the MIDAS approach is to express coefficients of the lags of the higher frequency indicators via a polynomial form. So, even if a researcher uses 50 lags of a daily indicator, only two or three parameters for a polynomial needs to be estimated. Then, coefficients can be obtained using this polynomial. Exponential Almon and Beta are two popular functional forms for lag polynomial. For the case of quarterly GDP and monthly indicators, since the number of lags that are need to be estimated are limited compared to financial applications that use daily data, it is suggested that rather than using a polynomial form, unrestricted coefficient estimates can be used as well which is named as U-MIDAS

(Foroni et al. 2015). In this paper, we analyze the nowcasting performance of several indicators for Turkish economy using MIDAS approach paying particular attention to the functional form of the lag polynomial.

Table 1. Polynomial Forms Used in the MIDAS Applications

Year of Publication	Authors	Target Variable	Beta	Exponential Almon	U-MIDAS	Stepfun	Almon
2008	Clements, Galvao	US GDP		+	+		
2009	Clements, Galvao	US GDP		+			
2010	Marcellino, Schumacher	German GDP		+	+		
2011	Kuzin, Marcellino, Schumacher	Euro Area GDP		+			
2013	Andreou, Ghysels,Kourtellos	US GDP		+			
2013	Galvao	US and UK GDP	+	+			
2013	Guerin, Marcellino	US GDP		+			
2013	Kuzin, Marcellino, Schumacher	GDP for USA, UK, Japan, Germany, France, Italy		+			
2014	Andrade, Fourel, Ghysels, Idier	Euro Area Inflation Risk	+	+			
2014	Bessec, Bouabdallah	US GDP		+	+		
2014	Foroni, Marcellino	Euro Area Macro Variables		+			
2014	Götz, Hecq, Urbain	US Inflation		+			
2015	Barsoum, Stankiewicz	US GDP		+	+		
2015	Baumeister, Guerin, Kilian	Oil Prices		+	+		
2015	Foroni, Marcellino, Schumacher	US GDP		+	+		
2015	Ghysels, Ozkan	US Fiscal Variables	+				
2016	Götz, Hecq, Urbain	US GNP		+			
2016	Jansen, Jin, de Winter	GDP for Euro Area, Germany, France, Italy, Spain, Netherlands		+			
2016	Schumacher	Euro Area GDP		+	+		
2016	Smith	UK Unemployment			+		
2017	Aastveit, Foroni, Ravazzolo	US GDP		+	+		
2017	Duarte, Rodrigues, Rua	Portugal Private Consumption	+	+	+		+
2018	Foroni, Guerin, Marcellino	US Inflation, Ind. Prod. and Personal Cons. Exp.		+	+		
2018	Kim, Swanson	Korean GDP		+	+		
2018	Tsui, Xu, Zhang	Singapore GDP	+				
2019	Hepenstrick, Marcellino	GDP for Several Developed and Emerging Economies			+		
2019	Knotek, Zaman	US Financial Variables	+	+	+		
2019	Kurz-Kim	Euro Area GDP			+		
2019	Şen-Doğan, Midiliç	Turkish GDP					+

Notes: Polynomial form used in the cited paper is denoted by "+" and highlighted with grey shading.

A review of the literature shows that there is not a consensus about the appropriate polynomial form to be used for MIDAS type regressions (Table 1). We see that MIDAS is mainly used for short-term forecasts of GDP but there are applications for inflation and unemployment rate as well. In terms of the polynomial form used, it is seen that exponential Almon dominates the list. Unrestricted-MIDAS (U-MIDAS) became relatively more popular over time. There are some applications that use Beta type polynomials. Almon or step function type weighting are either rarely used or are not employed at all. Most of the papers utilize one or two form of polynomials. So, we contribute to the literature by analyzing the effect of polynomial form on the forecasting performance in a comprehensive way.

Şen-Doğan and Midiliç (2019) use MIDAS based models for short-term forecasting of GDP growth in Turkey. Our study differs from this study in a number of ways. First of all, Turkish Statistical Institute (TURKSTAT) made major a revision in the GDP series. After the revisions in the GDP figures, level of GDP increased around 30 percent. Real growth rates changed considerably as well. Revisions to the data set is not limited to the GDP data. TURKSTAT made a substantial revision in the industrial production index as well. In addition to the revisions in the key macroeconomic variables, another difference of the present study is the composition of the data set structure. While Şen-Doğan and Midilic (2019)'s data set is mainly composed from daily financial series, our study looks at the so-called "hard-data" which are monthly indicators. We consider a wide range of indicators from production, turnover, foreign trade, sales, credit and public finance indicators. Analyzing the nowcasting performance of these widely monitored indicators is expected to inform forecasters and policy makers more about the forecasting power of these monthly indicators. Finally, Şen-Doğan and Midiliç (2019) note that Almon polynomial delivered the best results for their analysis while we explicitly present the effect of functional form of lag polynomial on the short-term forecast performance.

Our results indicate that depending on the forecast horizon, best performing specifications change in terms of the indicator, functional form of the lag polynomial and lag length of the high frequency indicator. Functional form of the polynomials play relatively more role for the shorter forecast horizons. Analyzing the best performing specifications across indicators show that Beta type polynomials perform relatively better than the popular exponential Almon. Increasing the lag length causes a deterioration for the performance of U-MIDAS while using around five lags makes U-MIDAS a competitive functional form. For longer forecast horizons, import quantity indices perform relatively better. As data accumulate for the target quarter, real domestic turnover and industrial production stand out in terms of short-term forecast performance. Analysis of the short-term forecasts of the best performing specifications show that they can track the developments in GDP quite successfully.

Structure of the paper is as follows. Next section discusses MIDAS methodology in more detail, then we introduce the data set used in the paper. After presenting forecast exercise design, we discuss results and then conclude.

2. METHODOLOGY: MIDAS REGRESSION APPROACH

In this section, we present details about the estimation of the equation used for nowcasting with MIDAS. Before going into technical details, we give some intuition. As pointed out by Schumacher (2016), MIDAS and the bridge equations are extensions of distributed lag models that enable us to work with a data set that is composed of indicators with different frequencies, such as monthly and quarterly. In the so-called bridge equation approach, a higher frequency indicator is converted to lower frequency by appropriate transformation, for example for flow variables by taking average. Then, this transformed series is used in a regression with quarterly GDP to estimate coefficients with ordinary least squares. Innovation in the MIDAS approach is to use all the indicators in their own frequency. Broadly, it can be thought of regressing, say, a quarterly variable onto a growth rate of the monthly indicator for a given number of months. Initially, MIDAS is developed for financial data where a monthly/weekly variable is regressed on a daily indicator. Since there are around 20 working-days in a month, this type of regression requires estimating a lot of coefficients. Ghysels et al. (2004) offered a solution to the parameter proliferation problem. They suggest that using certain functional form of the lag polynomial to estimate the coefficients. So, estimating 20 coefficients for daily observations can be reduced to estimating a few polynomial parameters.

After giving intuition, we present bridge equations. Based on this exposition, we will move to MIDAS approach. Using bridge equations, one can link monthly data with quarterly data as in the following equation (Angelini et al. (2011)) :

$$y_t^Q = \mu + \sum_{i=1}^{k} \beta_i^j(L) x_{it}^{jQ} + \varepsilon_t^{jQ} \tag{1}$$

Here, y_t^Q is the quarterly GDP growth, x_{it}^{jQ} is a monthly indicator transformed to quarterly frequency. Missing values of the x's are handled with separate forecasting procedures. These forecasts can be based on simple AR models or in some cases with more complicated models like BVAR models.

MIDAS approach uses the following type of equation.

$$y_{t+h}^{Q} = \beta_0 + \lambda y_t^{Q} + \beta_1 B\left(L^{\frac{1}{3}}, \theta\right) x_t^{m} + \varepsilon_{t+h} \tag{2}$$

where $B\left(L^{\frac{1}{3}}, \theta\right) = \sum_{k=0}^{K} b(k,\theta)\, L^{\frac{k}{3}}$

Here x_t^m is a monthly indicator, y is a quarterly indicator (since our aim is nowcasting quarter-on-quarter GDP growth) and h is the forecast horizon. Superscript 3 in the equation refers to the fact that we observe 3 values in the quarter for monthly indicator. Relation of the high frequency indicator with the low frequency indicator is denoted by indicator $\beta_1 B\left(L^{\frac{1}{3}}, \theta\right)$ where β_1 is a regression coefficient and $B\left(L^{\frac{1}{3}}, \theta\right)$ denotes the functional form of the lags. In non-technical terms, we explain the quarter-on-quarter GDP growth with month-on-month growth rate of monthly indicators. In the expression $\left(L^{\frac{1}{3}}, \theta\right) = \sum_{k=0}^{K} b(k,\theta)\, L^{\frac{k}{3}}$ we define how many lags of the indicator we use. If k=3, we use the last three months of the monthly indicator. For the case of observing June's industrial production, a MIDAS equation with three lags would use industrial production growth starting from June and going back to the April.

In general, monthly indicators for a quarter are published before the GDP growth for that quarter. Moreover, several monthly indicator become available before the end of the quarter. For instance, first month's industrial production data for a quarter are published in the third month of the quarter. So, we can use within quarter information for updating nowcasts. In order to take advantage of the early release of the indicators we can modify Equation 2. Let T_y show the last available observation for the quarterly GDP and T_x shows the date for the latest monthly data. Publication lags for monthly indicators are lower than publication lag for GDP so in general $T_x > T_y$. Schumacher (2016) defines number of monthly data available earlier than annual GDP data by $w = T_x - T_y$. So, MIDAS equation can be modified as follows which can be labeled as MIDAS with leads (Andreou et. al. (2013)). We use this framework for incorporating information from the target quarter.

$$y_{t+h}^{Q} = \beta_0 + \lambda y_t^{Q} + \beta_1 B\left(L^{\frac{1}{3}}, \theta\right) x_{t+w}^{m} + \varepsilon_{t+h} \tag{3}$$

In the MIDAS equation, a key input to choose before obtaining forecasts is functional form that is used to estimate the coefficients. Ghysels et al. (2004) proposed to obtain coefficients from a polynomial form. Over time, other alternatives that do not resort to polynomial forms emerged. We review several alternatives for functional form of the lags starting with exponential Almon lag which is a popular polynomial form (Table 1).

$$b(k;\theta) = \frac{\exp(\theta_1 k + \theta_2 k^2 + \cdots + \theta_q k^q)}{\sum_{j=0}^{K} \exp(\,\theta_1 j + \theta_2 j^2 + \cdots + \theta_q j^q)} \tag{4}$$

Ghysels et al. (2007) note that exponential Almon lag polynomials are flexible enough to cover hump-shape, declining or flat weights. Another popular polynomial type is Beta function. Two forms of this function are used.

$$\begin{aligned} w_i^{nz} = w_i(\theta_1, \theta_2, \theta_3) &= \frac{x_i^{\theta_1 - 1}\,(1 - x_i)^{\theta_2 - 1}}{\sum_{i=1}^{N} x_i^{\theta_1 - 1}\,(1 - x_i)^{\theta_2 - 1}} + \theta_3 \\ w_i^{z} &= w_i(\theta_1, \theta_2, 0) \end{aligned} \tag{5}$$

where superscripts *nz* and *z* show *non-zero last* and *zero last lags*, respectively and $x_i = (i1)/(N-1)$. In the empirical analysis, we use both Beta with non-zero and with zero (named as Beta) last lag type functions.

Exponential Almon and Beta type polynomials require non-linear least square estimation to obtain parameters. Next three alternatives that we present can be estimated using OLS. Almon lag polynomial is the first of this kind and it can be expressed as follows where θ denotes shape parameter (Ghysels (2013)):

$$\beta\omega_i\big(\theta_{0,}\,\ldots, \theta_p\big) = \sum_{p=0}^{P} \theta_p\, i^p \tag{6}$$

In addition to these functional forms, there are two alternative approaches for estimating the coefficients of higher frequency indicator, Unrestricted-MIDAS (U-MIDAS) and step function. Foroni et al. (2015) note that difference in sampling frequencies for the nowcasting GDP applications are not as large as financial applications. So, rather than obtaining coefficients via a polynomial form, they may be directly estimated. A forecasting equation with U-MIDAS can be expressed as follows which can be estimated with OLS.

$$y_{t+h}^{Q} = a + \delta_1(L) x_{t-1} + \varepsilon_t \tag{7}$$

where *y* is quarterly GDP and *x* is a monthly indicator. In words, we regress quarter-on-quarter growth rate on month-on-month changes.

Finally, one can use weights in the form of step functions. Ghysels and Marcellino (2018) express step function weights with K lags and S steps as in the following equation. This approach assigns equal weights to coefficients at each step. For example, if step size is 3 and 12 lags of month-on-month changes are used, then first three month-on-month changes will have the same coefficient, next three the same coefficient and so on. Step function approach can be considered as a middle ground between unconstrained estimation of U-MIDAS and polynomial forms such as Beta.

$$y_{t+h}^{L} = a_h + \lambda_h y_t^L + \sum_{k=0}^{K} \left(\sum_{s=0}^{S-1} c_s \, I_{k\in[a_{s-1},a_s]} \right) x_{t-k/m}^{H} + \varepsilon_{t+h}^{L}$$

$$I_{k\in[\alpha_{s-1},\alpha_s]} = f(x) = \begin{cases} 1, & \alpha_{s-1} \le k \le \alpha_s \\ 0, & otherwise \end{cases} \tag{8}$$

$$where\ a_0 = 0 < a_1 < \cdots < a_{S-1} = K$$

In addition to the functional form of the polynomial, lag length of the monthly indicators should be specified as well. Clements and Galvao (2009) consider 12 and 24 lags indicating using information from past year and past two years, respectively. Foroni and Marcellino (2014) fix the lag length to 12. Foroni et al. (2015) consider 6,12 and 24 lags in the MIDAS regressions. They find that U-MIDAS performs relatively better than a MIDAS equation using exponential Almon lag polynomial when 6 lags are used. So, we use lags from 5 to 12 to analyze the effect of lag specification on the short-term forecasting performance.

3. DATA

We use indicators from industrial production, real domestic turnover in industry, export and import quantity indices, electricity production, new job openings from a leading career website, sales of durable goods, credit, transaction volume in credit and debit cards, tax revenues and government spending (Table 2).

Table 2 lists the indicators that we use in the analysis and summarizes average and standard deviation for the quarter-on-quarter growth rate of these indicators. We also present the correlation of the indicators with GDP to get an idea about the strength of the relation of these two series. In addition to contemporaneous correlations, we present the correlation of GDP with lagged values of the indicators as well. In the last column, we present approximate publication lags.

Table 2. Descriptive Statistics for the GDP and Indicators Used in the Analysis (2006Q2-2019Q1)

	QoQ Growth Rates		Correlation of GDP Growth (t) and Indicator (t and t-1)		Approximate Publication Lag
	Average	Standard Deviation	t	t-1	Days After the End of the Month
IP-Total	1.1	3.0	**0.71**	0.17	40-45
IP-Intermediate	1.1	3.5	0.61	0.21	40-45
IP-Durable	1.1	6.0	0.64	0.03	40-45
IP-Nondurable	1.1	2.6	0.43	-0.03	40-45
IP-Capital	1.7	6.4	0.64	0.20	40-45
RDTI-Total	0.9	3.8	**0.79**	0.28	40-45
RDTI-Intermediate	0.9	4.2	**0.76**	0.22	40-45
RDTI-Durable	0.4	7.1	0.53	0.09	40-45
RDTI-Nondurable	1.2	2.5	0.52	0.16	40-45
RDTI-Capital	0.9	7.0	**0.73**	**0.43**	40-45
QX-Capital	1.9	8.3	0.32	0.14	40
QX-Consumption	1.2	3.3	0.31	0.16	40
QX-Intermediate excl. Gold	1.5	4.1	0.03	0.11	40
QX-Total excl. Gold	1.4	3.5	0.16	0.17	40
QM-Capital	0.2	8.0	0.39	0.28	40
QM-Consumption	0.4	7.1	0.42	**0.42**	40
QM-Intermediate excl. Gold	0.9	4.8	0.48	0.39	40
QM-Total excl. Gold	0.7	4.7	0.52	**0.44**	40
ELEC-Electricity	1.1	2.0	0.45	0.18	5-7
WG-Domestic Sales	0.8	10.2	0.24	0.27	17-22
CAREER-New Openings	2.1	8.2	0.55	**0.41**	5-7
VEH-Passenger Car Sales	1.3	18.7	0.19	0.35	5-7
VEH-Light Vehicle Sales	-0.5	17.5	0.30	0.34	5-7
VEH-Production	1.4	11.2	0.41	0.29	5-7
CR-Total (adj. for FX changes)	2.2	3.4	0.34	0.39	7-10
CR-Firm (adj. for FX changes)	2.2	3.4	0.30	0.37	7-10
CR-Housing	2.1	3.7	0.40	0.39	7-10
ETTE-Total	0.2	1.6	0.47	0.25	17-22
TAX-Total	0.8	3.6	0.49	0.38	15
GS-Total	1.4	2.8	0.16	0.04	15
GDP	1.1	2.2	1.00	0.12	60-70

Notes: Abbreviations used in the table: IP: Industrial production, RDTI: Real domestic turnover in the industry, QX: Export quantity index, QM: Import quantity index, ELEC: Electricity production (adjusted for weather effects), CAREER: Data from a career website, WG: White goods, VEH: Vehicles, CR: Real credit stock, ETTE: Index tracking volume of transactions of credit and debit cards (see Türkan (2008), TAX: Tax revenues, GS: Central government spending, GDP: Gross Domestic Product. Top 4 indicators in terms of correlation are highlighted with boldface.

Analysis of the correlations suggest that total real turnover in industry is the indicator with the highest contemporaneous correlation with GDP followed by real domestic turnover in intermediate goods and capital goods. Regarding the lagged correlations, import quantity index excluding gold has the highest correlation with GDP followed by consumption goods import quantity index and real domestic turnover in capital goods.

All series are used in seasonally adjusted form. If official series are available in seasonally adjustment form, such as industrial production, we use them. If official seasonally adjusted series are not available, we use TRAMO-SEATS for seasonally adjustment.

4. FORECAST EXERCISE DESIGN

We conduct pseudo-out-of-sample forecasting exercise to assess the forecasting performance. Since a real-time data set is not available, following the literature (such as Schumacher (2016)) we use the final vintage. Most of the indicators that we use start from January 2005 while there are some indicators, such as tax revenues and central government spending that start in 2006. Estimation periods for the MIDAS equations start from the earliest observation for each data set. We obtain short-term forecasts for 2014Q2-2019Q1 for a total of 20 quarters.

Forecasts are obtained in the recursive manner. For each quarter, we obtain nine forecasts. We present a stylized example for data availability, publication date and terminology in Table 3 for third quarter. We name the forecasting horizon, in terms of month, starting with the first available observation for a given month. For industrial production, July's realizations, which is the first month of the quarter, are published in September. So, we name nowcasts obtained when we observe July's realizations as h=0. In August, June's industrial production realizations are published and we denote them with h=+1 indicating that we do not observe a value for the quarter that we want to forecast and from the perspective of monthly data we are one month to see the first realization. h=-1 indicates that we observe the second month's realization for the target quarter.

Depending on the timing of prediction exercise, we can name predictions as forecasts, nowcasts and backcasts. For the case of third quarter, predictions produced in July, August and September are named as nowcasts, while predictions after the end of the quarter are named as backcasts. Predictions that are made before the start of the third quarter are denoted as forecasts. In the next section, when we need to refer to all of these three definitions, we use the expression "short-term forecasts". Note that for indicators with shorter publication lag than industrial production, such as tax revenues, we would shift the dates given in the shaded cells by one month.

As a benchmark we obtain forecasts from an AR model that uses lags of the GDP growth for 1 to 4 lags. Depending on the forecast horizon, we may need to obtain forecasts for more than one period ahead. For example, for h=+6 we need to forecast three quarter ahead. We use iterative forecasts for calculating short-term forecasts for GDP growth for more than one-period ahead forecasts.

Table 3. Example Time Line and Data Availability for Short-Term Forecasts of the Third Quarter

				Forecast for Q3				Nowcast for Q3			Backcast for Q3	
	Last Value for IP	**Last Value for GDP**	**Publication Date for IP**	h=+6	h=+5	h=+4	h=+3	h=+2	h=+1	h=0	h=-1	h=-2
Q1	Jan	Q4 of the previous year	March									
	Feb	Q4 of the previous year	April									
	Mar	Q4 of the previous year	May									
Q2	Apr	Q1	June									
	May	Q1	July									
	Jun	Q1	August									
Q3	Jul	Q2	September									
	Aug	Q2	October									
	Sep	Q2	November									
Q4	Oct											
	Nov											
	Dec											

Notes: Table shows the data availability, publication dates and terminology for short-term forecasts. Dates in the fourth column show the publication dates for the respective value for industrial production. For example, September's industrial production data are published in mid-November. Grey shaded areas show the available data. Predictions made in November would be denoted by h=-2 and named as backcast.

5. RESULTS

We have several dimensions in our analysis of short-term forecasting performance. Regarding the specification of the MIDAS equation, there are two dimensions of the analysis that may affect the short-term forecasting performance, namely lag length and functional form of the lag polynomial of the MIDAS equation. Another dimension is about the timing of the predictions that we classify as forecasts, nowcasts and backcasts. Overall, we analyze 30 different indicators, for six alternatives functional form of lag polynomial for estimating the coefficients of the lags from 5 to 12 and for the forecast horizons from h=+6 to h=-2. So, it is of interest to document which indicators performs best for short-term forecasting and which specifications lead to the best forecast performance for each indicator. We start with an example to show the different dimensions of the analysis. Consider the Root Mean Squared Errors (RMSE) given in the Table 4 for short-term forecasts of GDP with industrial production.

Table 4. Root Mean Squared Error with Different Polynomials for Industrial Production

		Lag5					
		Beta	Beta Non-Zero	Exp Almon	U-MIDAS	Stepfun	Almon
	h=+6	1.82	1.91	1.93	1.78	1.91	**<u>1.77</u>**
	h=+5	1.80	1.85	1.87	**<u>1.76</u>**	1.81	1.88
	h=+4	1.90	1.88	1.90	1.80	**<u>1.75</u>**	1.87
Forecast	h=+3	1.99	1.90	1.99	1.91	1.91	**<u>1.88</u>**
	h=+2	1.81	1.79	**<u>1.69</u>**	1.81	1.79	1.76
	h=+1	**<u>1.63</u>**	1.66	1.63	1.72	1.99	1.76
Nowcast	h=0	1.29	1.34	1.30	1.28	**<u>1.12</u>**	1.33
	h=-1	**<u>1.24</u>**	1.37	1.45	1.27	1.66	1.30
Backcast	h=-2	1.27	1.27	1.19	1.21	**<u>1.16</u>**	1.26
		Lag12					
		Beta	Beta Non-Zero	Exp Almon	U-MIDAS	Stepfun	Almon
	h=+6	1.82	**<u>1.81</u>**	1.84	2.15	1.88	1.88
	h=+5	1.85	1.82	1.88	1.89	1.78	**<u>1.78</u>**
	h=+4	1.86	1.85	1.90	1.87	**<u>1.83</u>**	1.86
Forecast	h=+3	1.97	1.97	1.99	2.03	**<u>1.94</u>**	1.96
	h=+2	1.83	1.75	1.80	**<u>1.72</u>**	1.80	1.85
	h=+1	1.62	1.79	1.63	**<u>1.55</u>**	1.99	1.77
Nowcast	h=0	1.33	1.33	1.30	1.37	**<u>1.16</u>**	1.44
	h=-1	**<u>1.34</u>**	1.79	1.70	1.61	1.63	1.73
Backcast	h=-2	1.49	1.35	1.29	**<u>1.29</u>**	1.44	1.37

Notes: Table shows the RMSE from out-of-sample forecasting exercise using industrial production for short-term forecasts of quarter-on-quarter GDP growth using five and twelve lags in the MIDAS equation. For each forecast horizon from h=6 to h=-2, lowest RMSE is underlined. See Table 3 for the definition of forecast horizons h=+6 to h=-2. Short-term forecasts errors for benchmark AR models that use only lags of the GDP growth are 1.87 for h=+6 to h=+1 and 1.97 for h=0 to h=-2.

For h=+6, indicating that we produce a forecast nine months before the publication of GDP growth for the third quarter, the smallest RMSE is obtained using Almon polynomial if we use five lags. On the other hand, for the case of using twelve lags, the lowest RMSE is obtained with Beta function with non-zero last lag as demonstrated in Equation 5. Comparing RMSEs for using five and twelve lags, it is seen that for h=+6, Almon polynomial form with five lags produce the lowest RMSE. For the case of h=-2 meaning that all of the three months' data are available for the quarter that we target, which would be two months after the end of the quarter, the lowest RMSE is obtained with step function and five lags. So, depending on the forecast horizon and functional form for estimating lags, best performing specifications changes.

Next, we consider RMSEs from all specifications. We start with the effect of polynomial form on the short-term forecasting performance for the pool of short-term forecasts. As an example, consider Table 4. For the case of using five lags, for h=+6 difference between maximum and minimum RMSE is 1.93-1.77= 0.16 while for h=-2 it is 0.11. We pool these results for all of the 30 indicators. Then, in Table 5 we show the average, maximum and minimum percentage difference between the lowest and the highest RMSE for all the indicators depending on the lag-length used. For example, for h=+6 and using five lags, average difference in the best and the worst RMSE is 9% while for h=-2 and twelve lags difference is 28%. This table shows that especially for forecasts, increasing the lag length of the monthly indicators increases the effect of polynomial form on the forecast performance. For, nowcasts and backcasts, polynomial form affect the short-term forecast performance of the indicator substantially both for the low and high lag lengths.

After documenting that short-term forecasting performance may change depending on the polynomial used, we move to the question of whether a particular polynomial form stand-out in terms of short-term forecasting performance. In Figure A.1 to A.3, we present the short-term forecasting results for five and twelve lags for all of the thirty indicators. Figures show that as the forecast horizon gets shorter, divergence in the forecasts increases both across indicators and among polynomial forms for each indicator. It is worth noting that short-term forecasts using U-MIDAS with twelve lags increases the short-term forecast error. This is in line with intuition of the using U-MIDAS such that when we use relatively low number of explanatory high frequency variables, directly estimating the coefficients, rather than restoring to non-linear estimation methods with exponential Almon or Beta type polynomials, may result in better forecast performance (Foroni et al. (2015)). It can be inferred from the results that using around five lags for U-MIDAS can be competitive while increasing the lag length to twelve causes a deterioration in the short-term forecast performance.

Table 5. Percentage Difference in the RMSE of Best and the Worst Performing Polynomial

Average

	h=+6	h=+5	h=+4	h=+3	h=+2	h=+1	h=0	h=-1	h=-2
Lag 5	0.09	0.09	0.12	0.14	0.16	0.18	0.23	0.20	0.18
Lag6	0.12	0.11	0.12	0.16	0.19	0.19	0.24	0.21	0.22
Lag 7	0.12	0.14	0.13	0.16	0.22	0.21	0.25	0.21	0.24
Lag 8	0.13	0.15	0.17	0.18	0.22	0.24	0.24	0.23	0.23
Lag 9	0.15	0.17	0.18	0.22	0.22	0.24	0.29	0.23	0.25
Lag 10	0.18	0.18	0.20	0.21	0.25	0.27	0.32	0.27	0.26
Lag 11	0.20	0.21	0.21	0.23	0.26	0.30	0.34	0.27	0.28
Lag 12	0.23	0.23	0.24	0.26	0.29	0.32	0.35	0.29	0.28

Max

	h=+6	h=+5	h=+4	h=+3	h=+2	h=+1	h=0	h=-1	h=-2
Lag 5	0.23	0.32	0.49	0.31	0.36	0.35	0.62	0.54	0.68
Lag6	0.25	0.36	0.41	0.41	0.47	0.35	0.53	0.57	0.57
Lag 7	0.27	0.37	0.44	0.34	0.49	0.39	0.69	0.49	0.66
Lag 8	0.29	0.44	0.48	0.55	0.64	0.51	0.69	0.61	0.58
Lag 9	0.43	0.45	0.58	0.54	0.51	0.43	0.86	0.60	0.62
Lag 10	0.54	0.57	0.54	0.64	0.61	0.58	0.77	0.69	0.58
Lag 11	0.45	0.90	0.58	0.55	0.72	0.66	0.80	0.65	0.76
Lag 12	0.52	0.64	0.95	0.54	0.59	0.82	0.81	0.71	0.68

Min

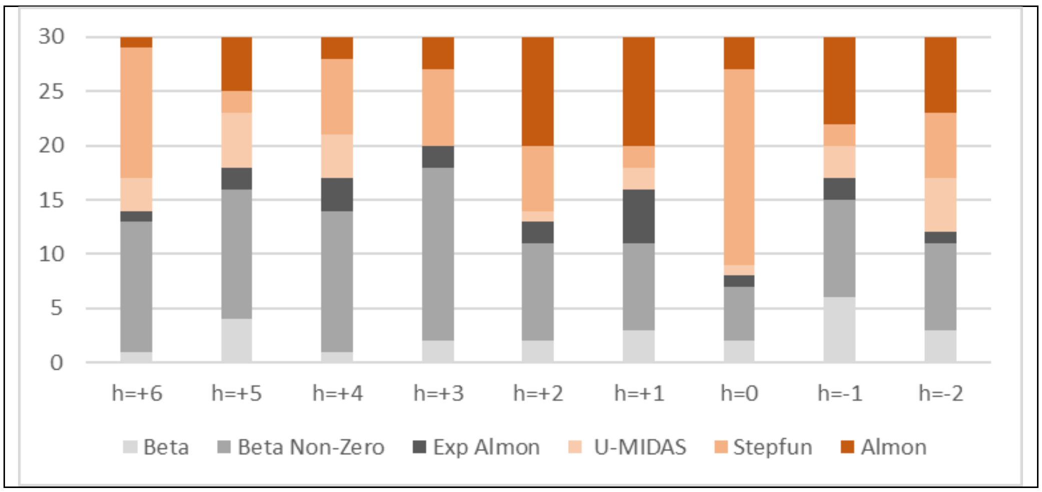
	h=+6	h=+5	h=+4	h=+3	h=+2	h=+1	h=0	h=-1	h=-2
Lag 5	0.01	0.02	0.02	0.03	0.06	0.05	0.03	0.02	0.02
Lag6	0.03	0.05	0.03	0.05	0.07	0.03	0.06	0.05	0.02
Lag 7	0.04	0.04	0.03	0.04	0.08	0.07	0.09	0.03	0.07
Lag 8	0.03	0.04	0.05	0.03	0.06	0.08	0.09	0.05	0.06
Lag 9	0.05	0.04	0.03	0.06	0.06	0.07	0.07	0.07	0.05
Lag 10	0.05	0.04	0.02	0.02	0.09	0.08	0.09	0.04	0.06
Lag 11	0.04	0.02	0.03	0.05	0.06	0.08	0.12	0.02	0.10
Lag 12	0.07	0.03	0.04	0.04	0.07	0.05	0.09	0.08	0.06

Notes: Entries in the cells are calculated as the average, maximum and minimum of (1-(Max RMSE/Min RMSE), respectively, for all the indicators considered in the analysis.

Next we present the results via tables to able to better spot the best performing specifications. In the Appendix, Table A.1 to Table A.3 presents the best specifications for each indicator for h=+6 to h=-2. For example, for industrial production for h=+6, step function with eleven lag produces the lowest RMSE while for h=+5, U-MIDAS with five lags produces the lowest RMSE. In Figure 1, we plot the number of times each polynomial appears in the best specification for the short-term forecast horizons we consider.

Exponential Almon and U-MIDAS, which are two popular polynomial forms used in the literature, appear relatively less frequently. Beta type polynomials, step function and Almon appear most in the best specifications. In Tables A.4 and A.5, we present the Diebold-Mariano test results for the statistical significance of the difference in forecast performance of five functional forms with respect to U-MIDAS. This analysis reveals that for some cases, U-MIDAS performs worse than other polynomial forms while it rarely performs relatively better and in several cases it performs as good as other functional forms. Therefore, while U-MIDAS approach can be a useful tool, depending on the indicator considered, care is still needed in the specification of functional form for applying MIDAS to forecasting Turkish GDP growth.

Figure 1. Number of Times Polynomial Form Appears in the Best Specification

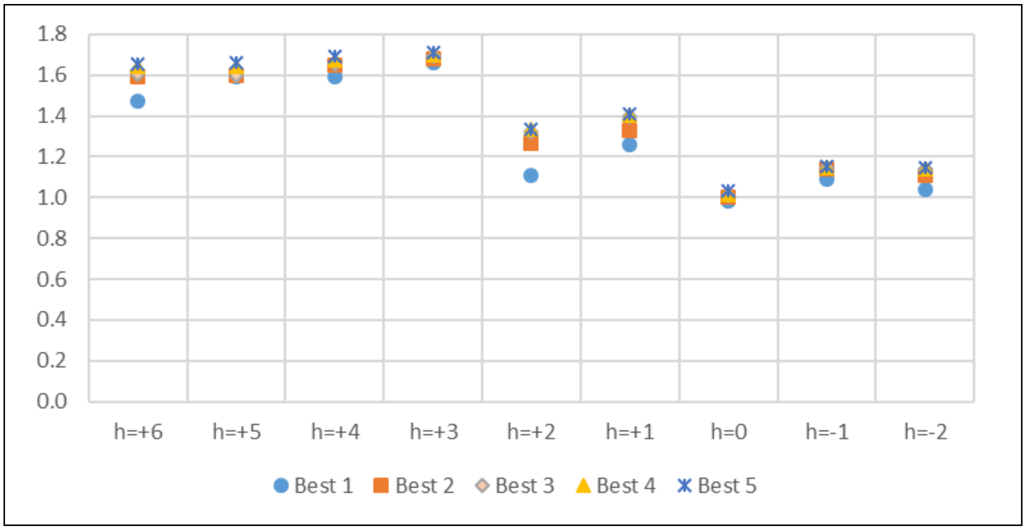


Notes: Figure shows the distribution of the best performing lag of the functional form of the lag polynomials for thirty indicators given in Table A.1 to A.3. For the definition of the functional forms see equations given in Section 2.

We also look at whether there are clusters in terms of best polynomial form such as production data performs better with a certain polynomial while foreign trade data with another type. This is indeed the case for some blocks. For example, for the four indicators from export quantity index best performing polynomial type are in general common. A similar observation is also valid for credit indicators. For industrial production and turnover in the industry there are relatively more heterogeneity in terms of the best polynomial type.

After documenting the findings regarding the functional form of the polynomial, we look at the best ten specifications, in terms of indicator, polynomial and lag length, for each horizon (Table A.6 and Table A.7). In Figure 2, we plot the RMSE for the best five specifications. We see that for h=+6 to h=+3 forecast errors are relatively higher and broadly stable around 1.6. As we show in Table 4, these are the forecasting horizons. For h=+2 and h=+1 which are nowcasting horizons but no data for the target quarter are available, RMSEs decline to around 1.2. For h=0 to h=-2 where monthly data for the target quarter enter into the information set, we observe RMSE around 1.0. Looking at the indicators used in the analysis, it is seen that import quantity indices stand out up to h=0 while for h=0 to h=-2 real domestic turnover indices appear in the best performing specifications list.

Figure 2. RMSE for the Best Five Specifications for Each Horizon



Notes: Figure shows the RMSE from out-of-sample forecasting exercise for the best performing specifications for the given forecast horizon for short-term forecasts of quarter-on-quarter GDP which are given in Table A.6 and Table A.7. See Table 3 for the definition of forecast horizons h=+6 to h=-2. Short-term forecast errors for benchmark AR models that use only lags of the GDP growth are 1.87 for h=+6 to h=+1 and 1.97 for h=0 to h=-2.

Lastly, we present the short-term forecasts for the best performing indicator in Figure 3 for all of the functional polynomial forms along with realizations of quarter-on-quarter GDP growth. This analysis will enable us to judge the success of the short-term forecasts visually. It is seen that for h=+0 to h=-2, short-term forecasts track GDP growth relatively successfully.

Figure 3. Short-Term Forecasts of Best Performing Specification for Each Forecast Horizons and Realizations

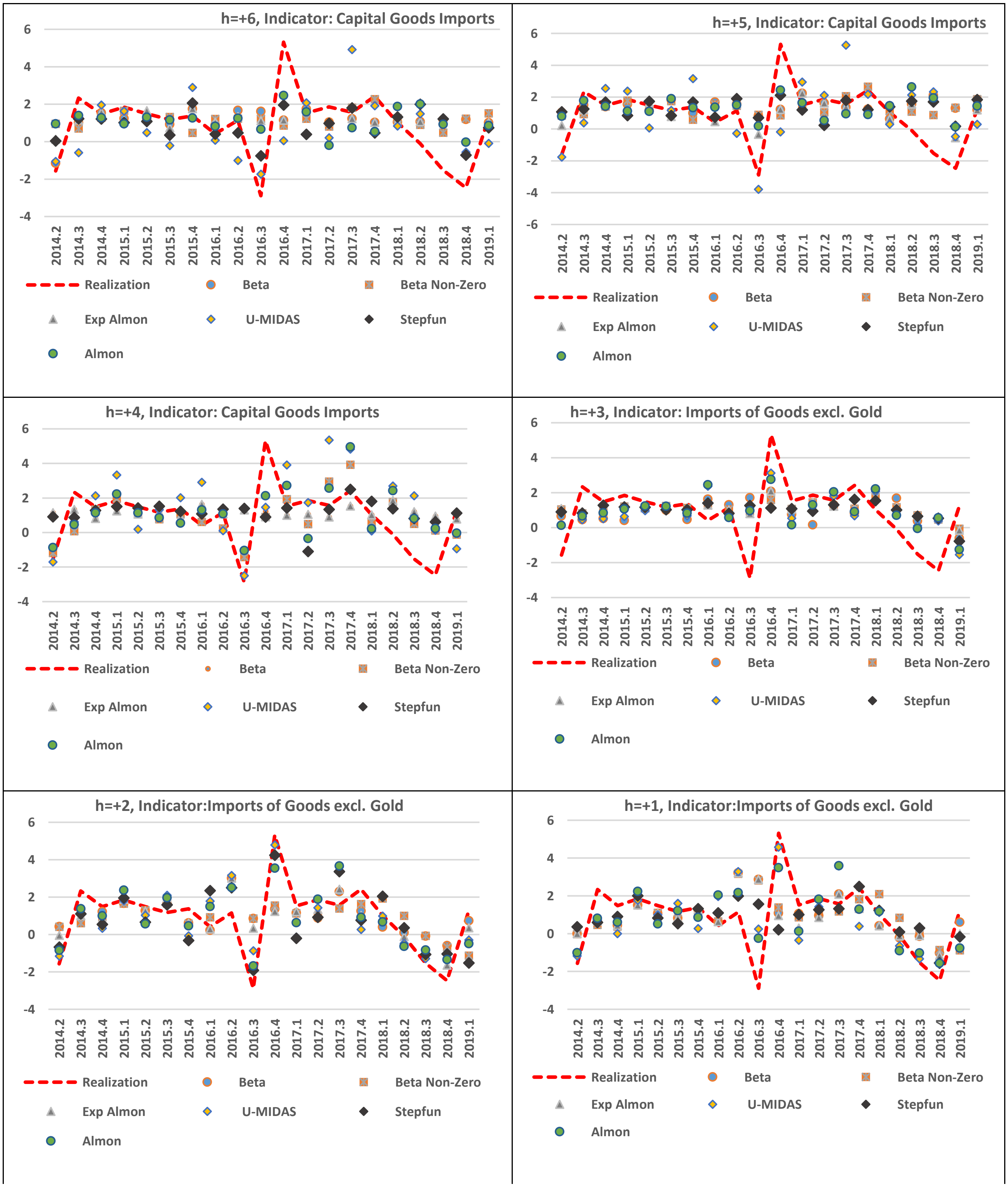


Figure 3. Short-Term Forecasts of Best Performing Specification for Each Forecast Horizons and Realizations (ctd.)

Notes: Figure shows the short-term forecasts of the indicators best-performing indicators that are given in Table A.4 for each forecast horizon.

6. CONCLUSION

In this paper we analyze short-term forecasts of quarter-on-quarter GDP growth for Turkish economy using with MIDAS approach. We pay particular attention to the effect of functional form of the lag polynomials. We find that Exponential Almon, which is a quite popular functional form used in the literature, does not perform well. Beta type polynomials perform relatively well for a lot of indicators. Unrestricted MIDAS, which do not impose a polynomial form on the lags of the high frequency indicator, with a low number of lags produces competitive forecasts. Our results indicate that before any realization is observed for monthly data for the target quarter, import quantity indices performs relatively well. Once data start to accumulate for the quarter that we want to forecast, real domestic turnover and industrial production indicators provides the best forecasts.

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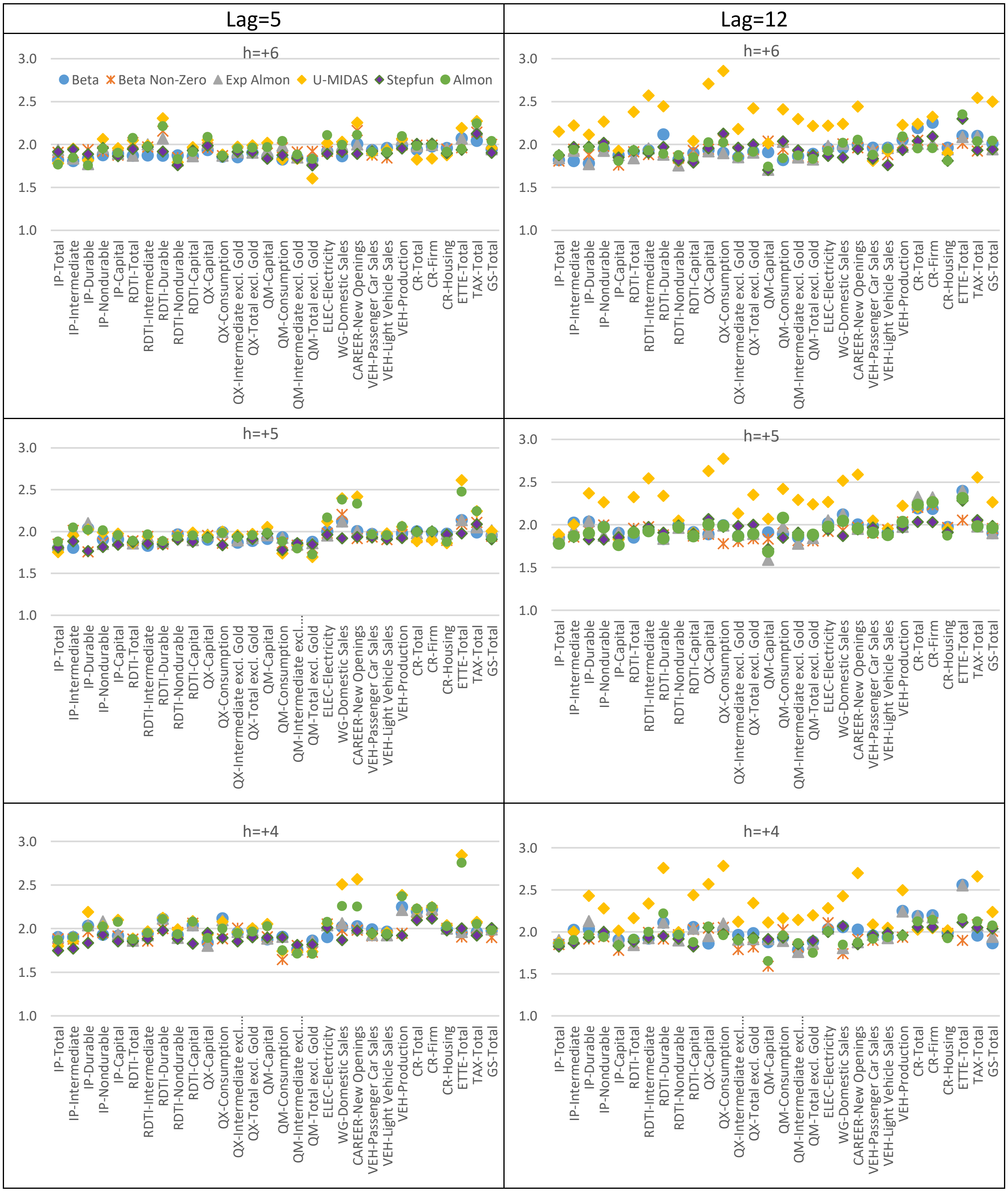
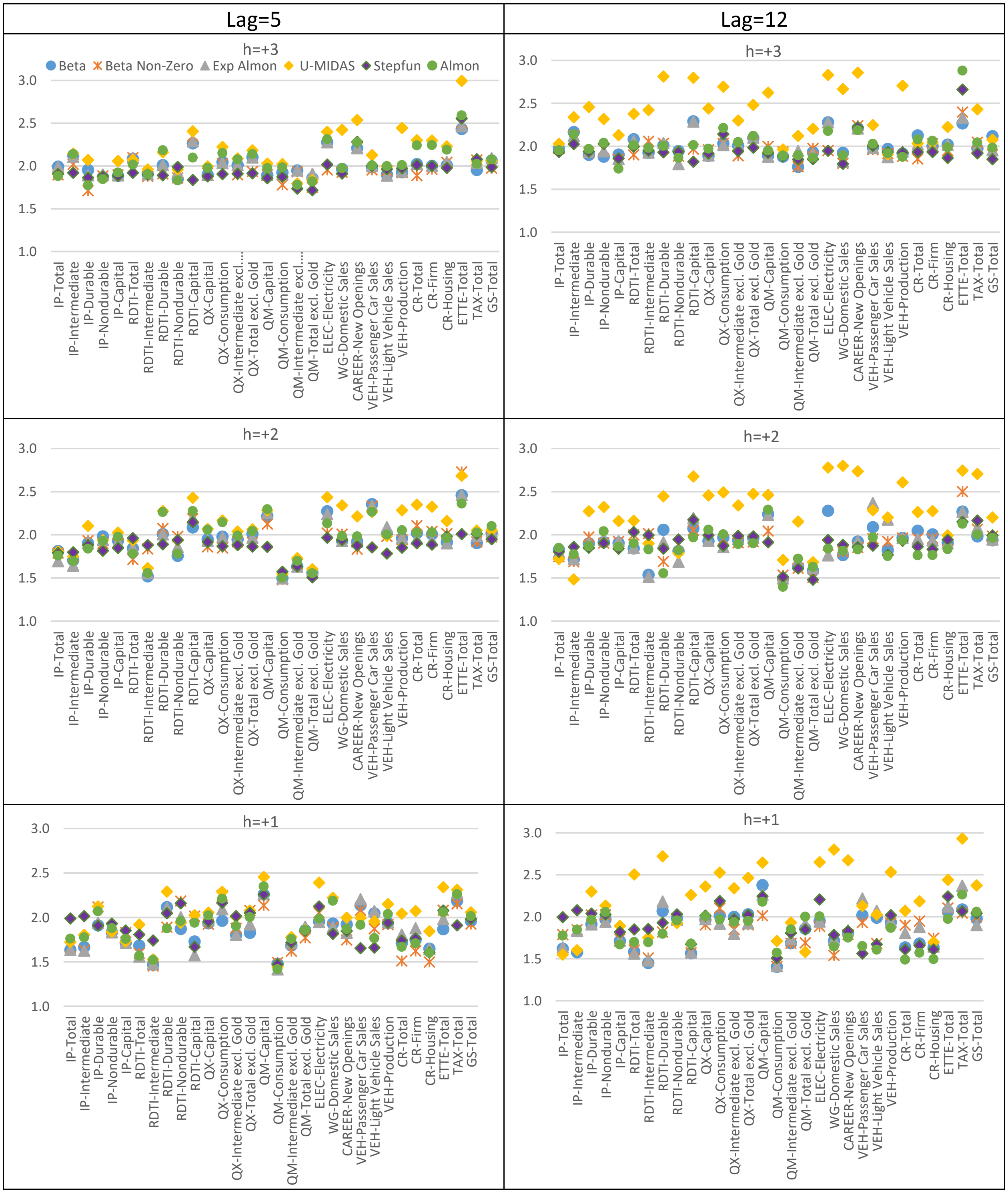
APPENDIX

Figure A. 1.RMSEs for Different Polynomial Forms for Five and Twelve Lags for h=+6 to h=+4



Notes: Please see Table 3 for a detailed explanation of the definition of the forecast horizons. h=0 refers to the case of observing first month's realization of monthly indicator for the target quarter. h=+X (h=-X) observing X less (more) month's realization relative to h=0.

Figure A. 2.RMSEs for Different Polynomial Forms for Five and Twelve Lags for h=+3 to h=+1



Notes: Please see Table 3 for a detailed explanation of the definition of the forecast horizons. h=0 refers to the case of observing first month's realization of monthly indicator for the target quarter. h=+X (h=-X) observing X less (more) month's realization relative to h=0.

Figure A. 3.RMSEs for Different Polynomial Forms for Five and Twelve Lags for h=0 to h=-2

Notes: Please see Table 3 for a detailed explanation of the definition of the forecast horizons. h=0 refers to the case of observing first month's realization of monthly indicator for the target quarter. h=+X (h=-X) observing X less (more) month's realization relative to h=0.

Table A. 1. Polynomial and Lag Specification with the Lowest RMSE for h=+6 to h=+4

	h=+6		h=+5		h=+4	
Indicator	Polynom	Lag	Polynom	Lag	Polynom	Lag
IP-Total	Stepfun	Lag11	U-MIDAS	Lag5	Stepfun	Lag5
IP-Intermediate	Beta Non-Zero	Lag11	Beta	Lag5	Stepfun	Lag5
IP-Durable	Almon	Lag5	Beta Non-Zero	Lag5	Beta Non-Zero	Lag6
IP-Nondurable	Beta Non-Zero	Lag11	Stepfun	Lag5	Stepfun	Lag6
IP-Capital	Stepfun	Lag11	Almon	Lag12	Stepfun	Lag10
RDTI-Total	Exp Almon	Lag10	Beta	Lag11	Stepfun	Lag6
RDTI-Intermediate	Beta	Lag5	Beta	Lag5	Beta Non-Zero	Lag5
RDTI-Durable	Beta Non-Zero	Lag8	Beta Non-Zero	Lag9	Beta Non-Zero	Lag10
RDTI-Nondurable	Stepfun	Lag7	Almon	Lag9	Almon	Lag9
RDTI-Capital	Stepfun	Lag10	Beta Non-Zero	Lag11	Stepfun	Lag11
QX-Capital	Beta Non-Zero	Lag7	Almon	Lag8	Exp Almon	Lag5
QX-Consumption	Stepfun	Lag5	Beta Non-Zero	Lag12	Beta Non-Zero	Lag9
QX-Intermediate excl. Gold	Beta Non-Zero	Lag10	Beta Non-Zero	Lag11	Beta Non-Zero	Lag12
QX-Total excl. Gold	Beta Non-Zero	Lag10	Beta Non-Zero	Lag11	Beta Non-Zero	Lag12
QM-Capital	Stepfun	Lag11	Exp Almon	Lag12	Beta Non-Zero	Lag12
QM-Consumption	Beta Non-Zero	Lag8	Beta Non-Zero	Lag9	Beta Non-Zero	Lag5
QM-Intermediate excl. Gold	Beta Non-Zero	Lag11	Exp Almon	Lag12	Almon	Lag5
QM-Total excl. Gold	U-MIDAS	Lag5	U-MIDAS	Lag6	U-MIDAS	Lag7
ELEC-Electricity (adj. for weather effect)	Stepfun	Lag8	Almon	Lag9	Beta	Lag5
WG-Domestic Sales	Stepfun	Lag9	Beta Non-Zero	Lag8	Beta Non-Zero	Lag12
CAREER-New Openings	Beta Non-Zero	Lag6	Beta Non-Zero	Lag7	Beta Non-Zero	Lag8
VEH-Passenger Car Sales	Beta Non-Zero	Lag6	Stepfun	Lag7	Exp Almon	Lag8
VEH-Light Vehicle Sales	Stepfun	Lag12	Beta Non-Zero	Lag8	Beta Non-Zero	Lag9
VEH-Production	Beta Non-Zero	Lag8	Beta Non-Zero	Lag9	Beta Non-Zero	Lag10
CR-Total (adj. for FX changes)	U-MIDAS	Lag8	U-MIDAS	Lag9	U-MIDAS	Lag10
CR-Firm (adj. for FX changes)	U-MIDAS	Lag8	U-MIDAS	Lag9	U-MIDAS	Lag10
CR-Housing	Stepfun	Lag12	U-MIDAS	Lag8	U-MIDAS	Lag9
ETTE-Total	Stepfun	Lag5	Beta Non-Zero	Lag6	Beta Non-Zero	Lag7
TAX-Total	Beta Non-Zero	Lag12	Beta	Lag8	Stepfun	Lag8
GS-Total	Stepfun	Lag9	Almon	Lag9	Exp Almon	Lag11

Notes: Table shows the polynomial form and lag length for each indicator. Alternating light and dark grey shading is used to differentiate changing data blocks.

Table A. 2. Polynomial and Lag Specification with the Lowest RMSE for h=+3 to h=+1

	h=+3		h=+2		h=+1	
Indicator	Polynom	Lag	Polynom	Lag	Polynom	Lag
IP-Total	Beta Non-Zero	Lag7	Almon	Lag6	Beta Non-Zero	Lag8
IP-Intermediate	Stepfun	Lag6	U-MIDAS	Lag10	U-MIDAS	Lag11
IP-Durable	Beta Non-Zero	Lag5	Beta Non-Zero	Lag6	Beta Non-Zero	Lag7
IP-Nondurable	Beta	Lag7	Stepfun	Lag5	U-MIDAS	Lag6
IP-Capital	Almon	Lag12	Stepfun	Lag12	Almon	Lag9
RDTI-Total	Beta Non-Zero	Lag12	Beta Non-Zero	Lag8	Exp Almon	Lag5
RDTI-Intermediate	Beta Non-Zero	Lag6	Beta	Lag9	Beta	Lag12
RDTI-Durable	Beta Non-Zero	Lag11	Almon	Lag12	Almon	Lag12
RDTI-Nondurable	Almon	Lag11	Exp Almon	Lag12	Beta	Lag5
RDTI-Capital	Stepfun	Lag11	Almon	Lag12	Beta Non-Zero	Lag11
QX-Capital	Beta Non-Zero	Lag6	Beta Non-Zero	Lag5	Beta Non-Zero	Lag10
QX-Consumption	Stepfun	Lag7	Almon	Lag8	Beta Non-Zero	Lag6
QX-Intermediate excl. Gold	Beta Non-Zero	Lag10	Beta Non-Zero	Lag11	Exp Almon	Lag7
QX-Total excl. Gold	Stepfun	Lag6	Almon	Lag7	Beta Non-Zero	Lag10
QM-Capital	Beta Non-Zero	Lag10	Stepfun	Lag6	Exp Almon	Lag11
QM-Consumption	Beta Non-Zero	Lag6	Stepfun	Lag7	Almon	Lag8
QM-Intermediate excl. Gold	Almon	Lag6	Almon	Lag7	Almon	Lag8
QM-Total excl. Gold	Exp Almon	Lag6	Almon	Lag7	Almon	Lag8
ELEC-Electricity	Beta Non-Zero	Lag11	Exp Almon	Lag7	Beta Non-Zero	Lag8
WG-Domestic Sales	Beta Non-Zero	Lag10	Beta Non-Zero	Lag11	Beta Non-Zero	Lag12
CAREER-New Openings	Beta Non-Zero	Lag9	Beta Non-Zero	Lag8	Almon	Lag11
VEH-Passenger Car Sales	Exp Almon	Lag9	Stepfun	Lag10	Stepfun	Lag11
VEH-Light Vehicle Sales	Beta Non-Zero	Lag10	Beta Non-Zero	Lag9	Exp Almon	Lag11
VEH-Production	Stepfun	Lag11	Stepfun	Lag5	Almon	Lag12
CR-Total (adj. for FX changes)	Beta Non-Zero	Lag12	Almon	Lag12	Almon	Lag12
CR-Firm (adj. for FX changes)	Beta Non-Zero	Lag7	Almon	Lag12	Almon	Lag12
CR-Housing	Stepfun	Lag11	Almon	Lag8	Almon	Lag11
ETTE-Total	Beta Non-Zero	Lag8	Beta Non-Zero	Lag8	Beta	Lag11
TAX-Total	Beta	Lag9	Beta	Lag6	Stepfun	Lag6
GS-Total	Stepfun	Lag12	Beta Non-Zero	Lag8	Exp Almon	Lag12

Notes: Table shows the polynomial form and lag length for each indicator. Light and dark grey shading is used to differentiate changing data blocks.

Table A. 3. Polynomial and Lag Specification with the Lowest RMSE for h=0 to h=-2

	h=0		h=-1		h=-2	
Indicator	Polynom	Lag	Polynom	Lag	Polynom	Lag
IP-Total	Stepfun	Lag10	Beta	Lag5	Stepfun	Lag5
IP-Intermediate	Stepfun	Lag6	U-MIDAS	Lag5	U-MIDAS	Lag5
IP-Durable	Stepfun	Lag10	Exp Almon	Lag11	Beta	Lag6
IP-Nondurable	Stepfun	Lag7	Beta Non-Zero	Lag5	Exp Almon	Lag5
IP-Capital	Exp Almon	Lag5	Beta	Lag5	Beta Non-Zero	Lag5
RDTI-Total	Stepfun	Lag10	Beta Non-Zero	Lag9	U-MIDAS	Lag5
RDTI-Intermediate	Stepfun	Lag5	U-MIDAS	Lag7	U-MIDAS	Lag5
RDTI-Durable	Stepfun	Lag6	Almon	Lag7	Beta	Lag12
RDTI-Nondurable	Stepfun	Lag12	Beta Non-Zero	Lag12	Beta Non-Zero	Lag5
RDTI-Capital	Beta	Lag5	Beta	Lag5	U-MIDAS	Lag5
QX-Capital	Beta Non-Zero	Lag10	Beta Non-Zero	Lag9	Stepfun	Lag7
QX-Consumption	Beta Non-Zero	Lag7	Beta	Lag9	Stepfun	Lag5
QX-Intermediate excl. Gold	Beta	Lag9	Exp Almon	Lag11	Beta Non-Zero	Lag5
QX-Total excl. Gold	Beta Non-Zero	Lag11	Beta	Lag9	Stepfun	Lag5
QM-Capital	Beta Non-Zero	Lag11	Beta Non-Zero	Lag7	Beta	Lag5
QM-Consumption	Stepfun	Lag5	Stepfun	Lag10	Almon	Lag10
QM-Intermediate excl. Gold	Stepfun	Lag8	Almon	Lag10	Almon	Lag10
QM-Total excl. Gold	U-MIDAS	Lag9	U-MIDAS	Lag10	U-MIDAS	Lag11
ELEC-Electricity	Stepfun	Lag5	Beta Non-Zero	Lag10	Stepfun	Lag5
WG-Domestic Sales	Stepfun	Lag5	Stepfun	Lag6	Stepfun	Lag5
CAREER-New Openings	Almon	Lag12	Beta Non-Zero	Lag11	Beta Non-Zero	Lag12
VEH-Passenger Car Sales	Stepfun	Lag9	Almon	Lag8	Almon	Lag7
VEH-Light Vehicle Sales	Stepfun	Lag9	Almon	Lag6	Beta Non-Zero	Lag9
VEH-Production	Beta Non-Zero	Lag9	Beta	Lag11	Beta Non-Zero	Lag11
CR-Total (adj. for FX changes)	Almon	Lag10	Beta Non-Zero	Lag11	Almon	Lag10
CR-Firm (adj. for FX changes)	Stepfun	Lag10	Beta Non-Zero	Lag11	Almon	Lag11
CR-Housing	Almon	Lag12	Almon	Lag9	Almon	Lag10
ETTE-Total	Stepfun	Lag5	Almon	Lag10	Almon	Lag11
TAX-Total	Stepfun	Lag7	Almon	Lag5	Beta Non-Zero	Lag10
GS-Total	Stepfun	Lag7	Almon	Lag10	Beta Non-Zero	Lag5

Notes: Table shows the polynomial form and lag length for each indicator. Light and dark grey shading is used to differentiate changing data blocks.

Table A. 4. Diebold-Mariano Test Results: Number of Cases U-MIDAS Performs Worse than Other Polynomials for Lags 5 to 12

	h=-2	h=-1	h=0	h=+1	h=+2	h=+3	h=+4	h=+5	h=+6
IP-Total	0	0	0	0	1	0	0	0	0
IP-Intermediate	0	0	1	0	0	0	0	0	0
IP-Durable	0	0	6	4	1	3	3	0	0
IP-Nondurable	0	0	0	0	2	2	0	2	1
IP-Capital	1	5	2	0	3	1	0	0	0
RDTI-Total	0	2	0	0	2	13	2	5	12
RDTI-Intermediate	1	3	0	0	0	3	6	9	14
RDTI-Durable	7	1	10	12	8	22	12	12	16
RDTI-Nondurable	0	1	0	0	2	0	0	0	0
RDTI-Capital	0	0	0	0	2	0	1	0	0
QX-Capital	3	0	1	4	7	16	19	20	28
QX-Consumption	3	3	4	12	12	19	17	22	27
QX-Intermediate excl. Gold	0	0	0	5	11	15	11	25	33
QX-Total excl. Gold	0	3	2	11	12	18	23	28	32
QM-Capital	0	0	0	0	0	12	20	2	2
QM-Consumption	1	1	1	0	0	0	2	1	1
QM-Intermediate excl. Gold	1	0	0	0	0	0	0	0	0
QM-Total excl. Gold	0	0	0	0	0	0	0	0	0
ELEC-Electricity (adj. for weather effect)	11	32	20	2	17	9	0	0	0
WG-Domestic Sales	25	21	22	17	30	36	29	18	0
CAREER-New Openings	7	12	19	33	35	28	24	1	0
VEH-Passenger Car Sales	7	16	26	14	5	4	0	0	0
VEH-Light Vehicle Sales	1	1	9	2	7	3	8	2	1
VEH-Production	0	0	0	0	0	0	9	7	4
CR-Total (adj. for FX changes)	7	7	16	22	15	1	0	0	0
CR-Firm (adj. for FX changes)	16	11	18	21	13	0	0	0	0
CR-Housing	0	0	0	7	4	1	0	0	0
ETTE-Total	0	2	1	0	3	2	1	1	0
TAX-Total	3	1	2	1	9	0	0	0	0
GS-Total	0	0	3	3	0	0	0	0	0

Notes: Table shows the Diebold-Mariano test results. We analyze six polynomial forms, namely Beta, Beta Non-Zero, Exponential Almon, Unrestricted MIDAS (U-MIDAS), Step function and Almon for lags 5 to 12. We take the U-MIDAS as benchmark and compare whether it produces statistically significant worse forecasts for a significance level of 0.05. For each lag length (from 5 to 12) we count the statistically significant differences of the forecast performance of the five functional forms for lag polynomials (with respect to U-MIDAS) and then sum these for eight lag specifications and report them in the cells.

Table A. 5. Diebold-Mariano Test Results: Number of Cases U-MIDAS Performs Better than Other Polynomials for Lags 5 to 12

	h=-2	h=-1	h=0	h=+1	h=+2	h=+3	h=+4	h=+5	h=+6
IP-Total	1	1	0	0	0	0	0	0	1
IP-Intermediate	0	0	0	0	0	0	0	0	0
IP-Durable	0	0	0	0	0	0	0	0	0
IP-Nondurable	0	0	0	0	0	0	0	0	0
IP-Capital	0	0	0	0	0	0	0	0	0
RDTI-Total	0	1	0	0	0	0	0	0	0
RDTI-Intermediate	0	0	0	0	0	0	0	0	0
RDTI-Durable	0	0	0	0	0	0	0	0	0
RDTI-Nondurable	0	0	0	0	0	0	0	0	0
RDTI-Capital	0	0	0	0	0	0	0	0	0
QX-Capital	0	0	0	0	0	0	0	0	0
QX-Consumption	0	1	0	0	0	0	0	0	0
QX-Intermediate excl. Gold	0	1	0	0	0	0	0	0	0
QX-Total excl. Gold	0	1	0	0	0	0	0	0	0
QM-Capital	1	0	0	0	0	0	0	0	0
QM-Consumption	0	0	0	0	0	0	0	0	1
QM-Intermediate excl. Gold	0	0	0	0	0	0	0	0	0
QM-Total excl. Gold	0	0	0	0	0	1	4	0	3
ELEC-Electricity (adj. for weather effect)	0	0	0	0	0	0	0	0	0
WG-Domestic Sales	0	0	0	0	0	0	0	0	0
CAREER-New Openings	0	0	0	0	0	0	0	0	0
VEH-Passenger Car Sales	0	0	0	0	0	0	0	0	0
VEH-Light Vehicle Sales	0	0	0	0	0	0	0	0	0
VEH-Production	0	0	0	0	0	0	0	0	0
CR-Total (adj. for FX changes)	0	0	0	0	0	0	0	0	1
CR-Firm (adj. for FX changes)	0	0	0	0	0	0	0	0	0
CR-Housing	0	0	0	0	0	0	0	0	2
ETTE-Total	0	0	0	0	0	0	0	0	0
TAX-Total	0	0	0	0	0	0	0	0	0
GS-Total	0	0	0	0	0	0	0	0	1

Notes: Table shows the Diebold-Mariano test results. We analyze six polynomial forms, namely Beta, Beta Non-Zero, Exponential Almon, Unrestricted MIDAS (U-MIDAS), Step function and Almon for lags 5 to 12. We take the U-MIDAS as benchmark and compare whether it produces statistically significant better forecasts for a significance level of 0.05. For each lag length (from 5 to 12) we count the statistically significant differences of the forecast performance of the five functional forms for lag polynomials (with respect to U-MIDAS) and then sum these for eight lag specifications and report them in the cells.

Table A. 6. Best Specifications for h=+6 to h=+3

h=+6					h=+5				
	Indicator	**Polynomial**	**Lag Legnth**	**RMSE**		**Indicator**	**Polynomial**	**Lag Legnth**	**RMSE**
Best 1	QM-Capital	Stepfun	Lag11	1.47	Best 1	QM-Capital	Exp Almon	Lag12	1.59
Best 2	WG-Domestic Sales	Beta Non-Zero	Lag10	1.59	Best 2	QM-Capital	Exp Almon	Lag11	1.60
Best 3	QM-Total excl. Gold	U-MIDAS	Lag5	1.61	Best 3	QM-Capital	Beta Non-Zero	Lag11	1.60
Best 4	QM-Capital	Exp Almon	Lag11	1.64	Best 4	QM-Total excl. Gold	U-MIDAS	Lag6	1.64
Best 5	QM-Capital	Almon	Lag11	1.65	Best 5	QM-Capital	Stepfun	Lag11	1.66
Best 6	RDTI-Capital	Stepfun	Lag10	1.66	Best 6	RDTI-Capital	Beta Non-Zero	Lag11	1.66
Best 7	RDTI-Durable	Stepfun	Lag10	1.67	Best 7	QM-Capital	Almon	Lag12	1.69
Best 8	RDTI-Capital	Stepfun	Lag11	1.67	Best 8	QM-Total excl. Gold	U-MIDAS	Lag5	1.70
Best 9	IP-Capital	Beta Non-Zero	Lag10	1.67	Best 9	QM-Consumption	Beta Non-Zero	Lag9	1.70
Best 10	WG-Domestic Sales	Exp Almon	Lag10	1.69	Best 10	QM-Capital	Almon	Lag11	1.70
h=+4					**h=+3**				
	Indicator	**Polynomial**	**Lag Legnth**	**RMSE**		**Indicator**	**Polynomial**	**Lag Legnth**	**RMSE**
Best 1	QM-Capital	Beta Non-Zero	Lag12	1.59	Best 1	QM-Total excl. Gold	Exp Almon	Lag6	1.66
Best 2	QM-Consumption	Beta Non-Zero	Lag5	1.65	Best 2	QM-Total excl. Gold	U-MIDAS	Lag8	1.68
Best 3	QM-Capital	Almon	Lag12	1.65	Best 3	QM-Total excl. Gold	Almon	Lag6	1.69
Best 4	QM-Total excl. Gold	U-MIDAS	Lag7	1.68	Best 4	QM-Consumption	Beta Non-Zero	Lag6	1.70
Best 5	QM-Consumption	Beta Non-Zero	Lag10	1.69	Best 5	RDTI-Nondurable	Almon	Lag11	1.71
Best 6	QM-Total excl. Gold	Almon	Lag5	1.71	Best 6	IP-Durable	Beta Non-Zero	Lag5	1.71
Best 7	QM-Intermediate excl. Gold	Almon	Lag5	1.71	Best 7	QM-Total excl. Gold	Beta Non-Zero	Lag6	1.71
Best 8	QM-Total excl. Gold	U-MIDAS	Lag6	1.72	Best 8	QM-Intermediate excl. Gold	Almon	Lag6	1.72
Best 9	QM-Intermediate excl. Gold	Almon	Lag11	1.73	Best 9	QM-Total excl. Gold	Stepfun	Lag5	1.72
Best 10	RDTI-Durable	Beta Non-Zero	Lag10	1.73	Best 10	QM-Consumption	Almon	Lag6	1.72

Table A. 7. Best Specifications for h=+2 to h=-2

h=+2					h=+1				
	Indicator	**Polynomial**	**Lag Legnth**	**RMSE**		**Indicator**	**Polynomial**	**Lag Legnth**	**RMSE**
Best 1	QM-Total excl. Gold	Almon	Lag7	1.11	Best 1	QM-Total excl. Gold	Almon	Lag8	1.26
Best 2	QM-Total excl. Gold	U-MIDAS	Lag7	1.27	Best 2	QM-Consumption	Almon	Lag8	1.33
Best 3	QM-Total excl. Gold	U-MIDAS	Lag8	1.32	Best 3	QM-Total excl. Gold	U-MIDAS	Lag8	1.39
Best 4	QM-Consumption	Stepfun	Lag7	1.33	Best 4	QM-Consumption	Beta	Lag12	1.40
Best 5	QM-Total excl. Gold	Stepfun	Lag7	1.34	Best 5	QM-Consumption	Beta Non-Zero	Lag12	1.41
Best 6	QM-Consumption	Almon	Lag12	1.39	Best 6	QM-Consumption	Exp Almon	Lag7	1.41
Best 7	QM-Consumption	Almon	Lag7	1.40	Best 7	QM-Consumption	Exp Almon	Lag9	1.41
Best 8	QM-Total excl. Gold	U-MIDAS	Lag9	1.41	Best 8	QM-Consumption	Exp Almon	Lag12	1.41
Best 9	QM-Total excl. Gold	Exp Almon	Lag7	1.44	Best 9	QM-Consumption	Exp Almon	Lag10	1.41
Best 10	IP-Intermediate	U-MIDAS	Lag10	1.44	Best 10	QM-Consumption	Exp Almon	Lag8	1.41
h=0					**h=-1**				
	Indicator	**Polynomial**	**Lag Legnth**	**RMSE**		**Indicator**	**Polynomial**	**Lag Legnth**	**RMSE**
Best 1	RDTI-Total	Stepfun	Lag10	0.98	Best 1	RDTI-Capital	Beta	Lag5	1.09
Best 2	RDTI-Total	Stepfun	Lag9	1.00	Best 2	RDTI-Capital	Beta	Lag11	1.14
Best 3	RDTI-Total	Stepfun	Lag11	1.01	Best 3	RDTI-Capital	Beta	Lag10	1.14
Best 4	RDTI-Total	Stepfun	Lag12	1.02	Best 4	RDTI-Capital	Beta	Lag9	1.15
Best 5	RDTI-Total	Stepfun	Lag6	1.04	Best 5	RDTI-Total	Beta Non-Zero	Lag9	1.15
Best 6	RDTI-Total	Stepfun	Lag5	1.04	Best 6	RDTI-Capital	Beta	Lag12	1.15
Best 7	RDTI-Total	Stepfun	Lag7	1.05	Best 7	RDTI-Capital	Beta	Lag8	1.15
Best 8	RDTI-Total	Stepfun	Lag8	1.06	Best 8	RDTI-Total	Beta	Lag7	1.16
Best 9	RDTI-Intermediate	Stepfun	Lag5	1.07	Best 9	RDTI-Capital	Beta Non-Zero	Lag11	1.19
Best 10	RDTI-Intermediate	Stepfun	Lag6	1.08	Best 10	RDTI-Capital	Beta	Lag6	1.19

h=-2				
	Indicator	**Polynomial**	**Lag Legnth**	**RMSE**
Best 1	IP-Intermediate	U-MIDAS	Lag5	1.04
Best 2	RDTI-Total	U-MIDAS	Lag5	1.11
Best 3	RDTI-Intermediate	U-MIDAS	Lag5	1.14
Best 4	RDTI-Capital	U-MIDAS	Lag5	1.14
Best 5	RDTI-Capital	Exp Almon	Lag5	1.15
Best 6	IP-Total	Stepfun	Lag5	1.16
Best 7	IP-Intermediate	U-MIDAS	Lag6	1.17
Best 8	RDTI-Capital	Beta	Lag6	1.17
Best 9	IP-Intermediate	U-MIDAS	Lag11	1.18
Best 10	IP-Intermediate	U-MIDAS	Lag12	1.18

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