Erasmus School of Economics
Master Thesis

Nowcasting US GDP Growth in 'Pseudo' Real Time Using Various Econometric Models

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February 28, 2019

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Abstract

The gross domestic product (GDP) is a quarterly released key indicator on the state of the economy and is subject to long publication delays. The Bureau of Economic Analysis (BEA) publishes the first estimate of GDP six weeks after the reference quarter. The uncertainty in between the releases stresses the importance to estimate current quarter GDP growth - nowcasting. In this paper I evaluate the real time performance of various econometric approaches to nowcast US GDP growth. In an extensive empirical study I find that the fairly unused methods in nowcasting LASSO and random projection regression overall perform best and are good alternatives to the well-established models in the nowcasting literature.

Keywords: Nowcasting, Dynamic Factor Model, Mixed-Data Sampling, LASSO, Random Projection

Contents

1 Introduction

The Great Recession during the financial crisis of 2008 was the largest recession the US economy had to face since the Great Depression in 1929. Most professional forecasters, statistical agencies and economists could not predict the "unexpected" turnaround of the US economy. Also more recent incidents show that there is a lot of uncertainty about detecting turning points in the business cycle. People fear that the controversial, volatile but confident economic decisions of current US president Donald Trump could lead to negligence of early signs of an upcoming recession. This puts an emphasis on the importance to assess the current state of the economy, where people rely heavily on the key indicator of economic activity - the Gross Domestic Product (GDP). However, GDP is quarterly released by the Bureau of Economic Analysis (BEA) and is subject to a substantial publication delay. In between the releases the real economic activity is uncertain and people need to rely on estimates of the current quarter GDP. Predicting the present value of GDP growth is known as 'nowcasting'.

Tracking macroeconomic conditions in real time faces several difficulties. Ever since statistical agencies started to collect data in every sector of the economy, the information set has grown enormously. Hence, nowcasting GDP is inherently a big data challenge. The goal is to produce and update weekly estimates of US GDP growth in a given quarter on basis of the flow of information that becomes available throughout the quarter. While the variable of interest, GDP growth, is available on a quarterly basis it can be estimated using a set of macro variables that are released at a higher frequency. The difficulty in producing the nowcasts in real time is threefold, (i) the dimensionality of the predictor set, (ii) the mixed frequency of the variables and (iii) the complicated pattern of the data set. The information set exhibits a "ragged" edge. Since macroeconomic variables follow an asynchronous publications schedule throughout the quarter, some variables have not been released at a specific time in the quarter, yielding many missing data entries at the end of the sample - a "ragged" edge.

In this paper I evaluate different econometric methods to nowcast US GDP growth in 'pseudo' real time based on a large set of macroeconomic indicators. The focus of this paper, in comparison to most papers in the nowcasting literature, is on the assessment of the real time performance during a quarter. Therefore, a 'pseudo' real time data set is used to imitate the data that would have been available in each respective time point. A caveat to a perfect real time evaluation is that the pseudo data set uses final data, hence ignoring data revisions. In the empirical application, weekly nowcasts are conducted and updated for 72 quarters in the period 2000 to 2017. Moreover, to evaluate how the models perform in shock scenarios, I divide the period into one before the Great Recession and one after it, respectively. To best of my knowledge no paper conducts this comprehensive comparison of models in a weekly nowcast setting.

The relatively new literature on nowcasting GDP growth in real time builds upon the work of Giannone, Reichlin, and Small (2008). They proposed a Dynamic Factor Model in state space representation in order to make use of Kalman filter techniques. It provides a parsimonious model that overcomes the 'curse of dimensionality' by summarizing the data in a few unobserved factors that describe the common dynamics of the macroeconomic indicators. However, due to the difficult pattern of the data set, factor estimation is a challenge and several estimation procedures have been proposed. The most common used techniques are the two-step estimator introduced by Doz, Giannone, and Reichlin (2011) and a modified expectation maximization (EM) algorithm proposed by Bańbura and Modugno (2014). Marcellino and Schumacher (2010) find in their empirical study that there is

no superior factor estimation procedure in terms of nowcasting accuracy. The state space representation and Kalman filtering techniques subsequently allow conveniently to produce projections of all variables and deal with the ragged edge feature of the data set by putting no weight on these entries. The Dynamic Factor Model is the workhorse model for many central banks and other institutions to assess the current state of the economy to make educated monetary policy decisions (see e.g.: Bok, Caratelli, Giannone, Sbordone, and Tambalotti (2018), Aastveit and Trovik (2012), D'Agostino, McQuinn, and O'Brien (2011), Yiu and Chow (2010) and Arnoštová, Havrlant, Ržička, and Tóth (2011)).
Another approach to tackle the mixed frequency data set has been introduced by Ghysels, Santa-Clara, and Valkanov (2004). The mixed-data sampling (MIDAS) regression allows regressor and regressand to be sampled at different frequencies and has proven to be useful in macroeconomic forecasting (e.g.: Ghysels, Sinko, and Valkanov (2007), Clements and Galvão (2008), Kuzin, Marcellino, and Schumacher (2011)). A parsimonious specification is guaranteed when the right lag polynomial is employed. Literature suggests an exponential Almon lag polynomial with two parameters for nowcasting GDP growth (e.g.: Clements and Galvão (2008), Armesto, Engemann, and Owyang (2010), Bańbura, Giannone, Modugno, and Reichlin (2013)). In order to apply MIDAS regression in real time, Marcellino and Schumacher (2010) proposed a Factor-MIDAS approach, in which, analogously to the Dynamic Factor Model, the dynamics of the macroeconomic indicators are described by a few latent factors and subsequently a MIDAS regression is applied to obtain the nowcast. A priori, one would expect this approach to be more accurate as it exploits all available information.
Additional to the well-known models in the nowcasting literature, also Bayesian methods have been applied to nowcast GDP growth in real time. One the one hand, Bayesian shrinkage methods have been used (Carriero, Clark, and Marcellino (2015), Kapetanios, Marcellino, and Papailias (2016)), as well as Bayesian vector autoregressive models (BVAR) (Schorfheide and Song (2015), Itkonen, Juvonen, and Petteri (2017)) .
Furthermore, I contribute to existing literature by exploring the nowcasting power in real time of the fairly unused methods *random projection regression* (RP) and *least absolute shrinkage and selection operator* (LASSO). The random projection regression is a rather naive model reduction technique, where a random matrix is used to reduce the dimensionality of the regressor space. In the forecasting literature it has not yet found many applications (see e.g.: Boot and Nibbering (2017)). LASSO overcomes the 'curse of dimensionality' by selecting informative predictors and setting the remaining coefficients of uninformative indicators equal to zero.
Assessing the nowcasting accuracy in real time over 72 quarters in the period of 2000Q1 - 2017Q4, in which for each model $22 \times 72 = 1584$ nowcasts are made, I find that the random projection method and LASSO perform overall best. The difference in performance of these two is minimal, while the random projection regression performs slightly better in the period 2000Q1 - 2007Q3, LASSO does in the period 2007Q4 - 2017Q4. To get an idea of the relative accuracy of the models, the Dynamic Factor Model (DFM) is used as a benchmark. Beside these two models also the unrestricted-Factor-MIDAS (UFAMIDAS) is able to beat the benchmark in the period before the Great Recession. Only the Factor-MIDAS (FAMIDAS) approach is consistently unable to beat the benchmark and performs overall worst.
The remainder of the paper is structured the following way: Section 2 defines the methodology of the nowcasting models, Section 3 describes the data and the set up of the 'pseudo' real time data set. In Section 4, I present the empirical study and its results. Section 5 concludes.

2 Nowcasting Models

2.1 Dynamic Factor Model

The first model I propose to use to estimate GDP growth in real time is a Dynamic Factor Model introduced by Giannone et al. (2008). The main idea of Dynamic Factor Models is that the dynamics of many observed variables can be explained by a few unobserved factors. Due to the co-movement of the macroeconomic indicators, a few factors capture the bulk of joint fluctuations of the series (e.g.: Giannone, Reichlin, and Sala (2004), Sargent and Sims (1977)). Moreover, the Dynamic Factor Model provides a parsimonious framework that can handle large irregular, spaced data sets. Summarizing the data in a few common factors limits the number of parameters to estimate. Additionally, the dynamics of the factors are explicitly modeled as a vector autoregression, which are driven by a white noise process.
The model can be cast in a state space representation:

$$X_t = \Lambda F_t + \zeta_t, \qquad \zeta_t \sim N(0, \Sigma_\zeta) \tag{1}$$
$$F_t = AF_{t-1} + Bu_t, \qquad u_t \sim N(0, I_q) \tag{2}$$

where the transformed stationary macroeconomic series $X_{i,t}$ are modeled as sum of two unobserved orthogonal stochastic processes: the common component $\sum_{i=1}^{r} \lambda_{i,t} f_{i,t}$ where $r \ll n$ factors explains the bulk of co-movements and the idiosyncratic disturbance ζ_t that captures variable-specific shocks. The matrix Λ contains the factor loadings, whereas the dynamics of the factors are explained by a matrix A - a $r \times r$ matrix with all roots of $det(I_r - Az)$ outside the unit circle - and a q-dimensional white noise process u_t. To maintain a parsimonious representation, the additional assumption that the idiosyncratic components are cross-sectionally uncorrelated, is assumed:

$$E[\zeta_t \zeta_t^{'}] = \Psi_t = diag(\tilde{\psi}_{1,t}, ..., \tilde{\psi}_{n,t}) \tag{3}$$
$$E[\zeta_t \zeta_{t-s}^{'}] = 0 \ , \ \ \forall s > 0 \tag{4}$$

and the idiosyncratic components are orthogonal to white noise process u_t:

$$E[\zeta_t u_{t-s}^{'}] = 0 \ , \ \ \forall \ s \tag{5}$$

As mentioned before, the data set exhibits a ragged edge, yielding many missing data entries at the end of the sample. In order to handle these observations, the variance of the idiosyncratic component is defined by:

$$\tilde{\psi}_{i,t} = \begin{cases} \psi_i & \text{if } x_{i,t} \text{ is available,} \\ \infty & \text{if } x_{i,t} \text{ is missing.} \end{cases} \tag{6}$$

Together with the additional assumption that GDP growth and the indicators are jointly normal, the nowcast is obtained via an OLS regression of GDP growth on the expected common factors.

$$\hat{y}_{t_j} = \alpha + \beta \hat{F}_{t_j}, \tag{7}$$

with $\hat{F}_{t_j} = E[F_{t_j} | \Omega_{t_j}]$, where subscript j indicates the week in the updating period and Ω_{tj} the corresponding information set. Due to the ragged edge of the data set in real time, obtaining $\hat{F}_{t_j}$ is a challenge. In recent literature, multiple methods have been introduced that can tackle this issue. However, Marcellino and Schumacher (2010) show in their empirical application that different estimation techniques do not yield substanially different results. Hence, I focus on the two-step procedure proposed by Giannone et al. (2008).

The state space representation of the Dynamic Factor Model enables to make use of Kalman filtering techniques. The Kalman filter provides a way of dealing with missing observations at the end of the sample, by putting no weight on missing observations (Equation 6). In the first step of the procedure, the model parameter given in the Equations 1-2 are estimated. Therefore, a principal component analysis on the observed data is conducted and the principal components are used as an approximation for F_t, denoted by $\tilde{F}_t$. The factor loading estimate $\hat{\Lambda}$ is obtained via an OLS regression on the principal components. The vector autoregression of order 1, described in the state-transition Equation 2, is fit with $\tilde{F}_t$. The second step produces the expected values of the common factors. Therefore, the estimated model parameters are used to initialize the the Kalman Filter. Subsequently the Kalman Smoother updates the predictions.

Model Specification

I follow Bok et al. (2018) and use a Dynamic Factor Model with one common factor to nowcast GDP growth in real time. Additionally to the common factor - labeled as global (G) -, three local blocks are included in the model to deal with the idiosyncratic characteristics of the subgroups. The first local block is the soft block (S) affecting the variables that belong to soft data releases, like ISM surveys, and two additional blocks real (R), affecting series that cover real economic activity, like the real gross domestic product (GDP) or the industrial production index and a labor block (L), covering variables that describe the labor market, for example the unemployment rate. The specifications applied to this model can be found in the structure of the factor loading matrix, see Table 8 in the Appendix, where a 1 is indicating that the variable in question is part of the respective subgroup.

2.2 Mixed-Data Sampling

In the mixed-data sampling regression, henceforth MIDAS, regressand and regressors do not need not be sampled at the same frequency. Moreover, with the right choice of the distributed lag polynomial, a parsimonious specification is guaranteed.

For the sake of presentation, I assume that there is one regressor x_{t_m} at monthly frequency that is used in the MIDAS regression. The regressand at quarterly frequency y_{t_q} can be expressed in a monthly manner if we set $y_{t_m} = y_{t_q}$, $\forall t_m = 3t_q$. Hence, we relate the x_{t_m}'s to the months when the lower frequency variable y_{t_q} is available. Following the notation of Kuzin et al. (2011), the simple MIDAS regression can be expressed as:

$$y_{t_q} = y_{t_m} = \beta_0 + \beta_1 b(L_m, \theta) x_{t_m}^{(3)} + \varepsilon_{t_m}, \quad \forall t_m = 3t_q$$

where $b(L_m, \theta)$ is some lag polynomial of order K that has the general form of

$$b(L_m, \theta) = \sum_{k=0}^{K} c(k, \theta) L_m^k.$$

The monthly lag operator $L_m^k(x_{t_m})$ produces lagged values of x_{t_m} by k periods. Therefore the lag polynomial $b(L_m, \theta)x_{t_m}^k$ consists of every k^{th} lagged value of x_{t_m} up to the maximum order of K : $b(L_m, \theta)x_{t_m}^k = (x_{t_m-k}, x_{t_m-2k}, \ldots, x_{t_m-Kk})$. The main advantage of the MIDAS regression is that we can link quarterly GDP growth y_{t_q} to lower frequency explanatory variables and their lags and use all available observations. However, this can make estimation unfeasible due to the number of parameters to estimate. In order to maintain a parsimonious specification, the choice of the lag polynomial is crucial. Ghysels et al. (2004) introduced a flexible lag polynomial that reduces number of parameter to estimate. The exponential Almon lag polynomial has following general form:

$$c(k, \theta) = \frac{exp(\theta_1 k + \theta_2 k^2 + \cdots + \theta_r k^r)}{\sum_{k=1}^{K} exp(\theta_1 k + \theta_2 k^2 + \cdots + \theta_r k^r)}. \tag{8}$$

There is wide range of polynomials that are suited to overcome to curse of dimensionality. In the forecasting literature the exponetial Almon lag has proven to be useful (e.g.: Clements and Galvão (2008), Armesto et al. (2010), Bańbura et al. (2013)). For further discussion on different lag polynomials, the reader is referred to Ghysels et al. (2007). The price of the parsimonious specification is that the model becomes non-linear and can be estimated using non-linear least squares (NLS), yielding $r + 2$ estimates $(\hat{\theta}_1, \ldots, \hat{\theta}_r, \hat{\beta}_0, \hat{\beta}_1)$.

The MIDAS approach is a direct forecasting tool yielding horizon-specific models. This is because the dynamics between regressors and regressand are not explicitly modelled (Kuzin et al., 2011).

In the following, I focus on two extended MIDAS approaches: the Factor-MIDAS and the unrestricted Factor-MIDAS.

2.2.1 Factor-MIDAS

The Factor-MIDAS (henceforth FAMIDAS) proposed by Marcellino and Schumacher (2010) combines two econometric methods used in nowcasting: Mixed-Data Sampling and Dynamic Factor Models. While the nowcast of the in Section 2.1 described DFM is based on the factors when GDP growth is observed, the FAMIDAS approach exploits all available observations of the common factor and its lags. The FAMIDAS approach is therefore a MIDAS regression in which the regressor is the common factor of the macro-indicators. Analogously to the Dynamic Factor Model one common factor is used in this model. The estimation of the common factor follows the two-step procedure described in Section 2.1. The model can be formulated as:

$$y_{t_q} = y_{t_m} = \beta_0 + \beta_1 b(L_m, \theta) f_{t_m}^{(K)} + \varepsilon_{t_m},$$

where I use for $b(L_m, \theta)$ an exponential Almon Lag polynomial of order K with two parameters, that is:

$$c(k, \theta) = \frac{exp(\theta_1 k + \theta_2 k^2)}{\sum_{k=1}^{K} exp(\theta_1 k + \theta_2 k^2)}. \tag{9}$$

Beside the choice of the lag function, the maximum order K of the polynomial is of great importance. For this purpose we use a model selection procedure, in which the model selects the maximum order based on the Akaike information criterion (AIC).

2.2.2 Unrestricted Factor-MIDAS

The unrestricted Factor-MIDAS (henceforth UFAMIDAS) approach can be regarded as a generalization of the FAMIDAS and an extension of the DFM model. The UFAMIDAS is a MIDAS regression, which analogously to the FAMIDAS, uses the common factor as regressor but does not employ an exponential lag polynomial. The quarterly GDP y_{t_q} is linked to the factor f_t and to the factors of the respective quarter f_{t_m-1} and f_{t_m-2}. Therefore, this MIDAS regression is superior in the sense that it exploits all available observations and not only those observations when GDP is observed. The model can be stated as:

$$y_{t_q} = y_{t_m} = \alpha_0 + \alpha_1 \hat{f}_{t_m} + \alpha_2 \hat{f}_{t_m-1} + \alpha_3 \hat{f}_{t_m-2} + \epsilon_{t_m} \tag{10}$$

The UFAMIDAS model employed in the empirical application uses the same common factor as the DFM and FAMIDAS approach.

2.3 LASSO

The focus so far was solely on statistical models that captured the factor structure of the data. Another approach to overcome the curse of dimensionality is the 'Least Absolute Shrinkage And Selection Operator', henceforth LASSO. The LASSO, introduced by Tibshirani (1996), combines variable selection and regularization by setting the coefficients of non-informative variables to zero, while shrinking the remaining coefficients. The LASSO is a general method that can be applied to a variety of models. For my purposes, I use the LASSO in a linear model, which can be regarded as an extension of the OLS regression. This penalized likelihood approach minimizes the sum of squared residuals under the restriction that the absolute sum of the coefficients is smaller than a constant:

$$arg \min_{\beta} ||Y - X\beta||_2^2 \qquad \text{subject to} \qquad ||\beta||_1 < t,$$

where the tuning parameter $t > 0$ determines the degree of shrinkage. The minimization problem can be equivalently formulated:

$$arg \min_{\beta} ||Y - X\beta||_2^2 + \lambda||\beta||_1,$$

with a penalty term $\lambda \geq 0$. As one can easily notice, in case of $\lambda = 0$, it is a standard OLS regression. Increasing the value of λ forces coefficients to be zero inducing a dimension reduction. On the other hand, an increasing λ increases also the bias, which stresses the importance of the choice of λ. To find the optimal λ in terms of prediction accuracy, I use a cross-validation scheme. Cross-validation uses in-sample data to achieve highest out of sample accuracy. The idea is to divide the sample into k folds and remove one fold of the sample. The $k - 1$ folds are used to estimate models for a grid of λ values. The accuracy of the grid of models is tested on the remaining fold. Iterating this procedure for each of the k folds and selecting the λ that yields the lowest out-of sample prediction error defines the optimal tuning parameter.

2.4 Random Projection

Finally, I introduce the random projections regression (henceforth RP), a rather naive approach to reduce the dimensionality of the predictor set. It is a fairly unused method in macroeconomic forecasting and nowcasting, but has proven its forecasting abilities already in empirical studies (e.g.: Elliott, Gargano, and Timmermann (2013), (2015)). The idea is to project the high dimensional predictor space $X \in \mathbb{R}^{N \times T}$ on the low dimensional subspace $\tilde{X} \in \mathbb{R}^{p \times T}$, where $p \ll N$. The subspace $\tilde{X}$ is generated by averaging over the predictors with randomly assigned standard normal weights:

$$\tilde{X} = RX \qquad R \in \mathbb{R}^{p \times N}$$
$$R_{ij} \sim N(0, p^{-\frac{1}{2}})$$

To obtain a nowcast an OLS regression of GDP growth on the low dimensional subspace is conducted:

$$y = \alpha + \beta\tilde{X} + \varepsilon$$

Repeating this simple procedure K times and averaging over these K estimates produces the final nowcast. In order to get accurate nowcasts the value of K needs to be sufficiently large. I decided, to average over 1000 random projection regression to obtain a single nowcast.

3 Data

The nowcasting model currently employed by the Federal Bank of New York, described in the paper by Bok et al. (2018), uses a data set rich of macroeconomic information. I follow Bok et al. (2018) and use the same set of 36 indicators that cover a wide range of real economic activity in the US, including industrial production, the labor market, domestic production, manufacturing and domestic and international trade. It includes both soft data, that is qualitative information obtained from surveys, polls or ratings and hard data, that is quantitative information and directly measurable. In this nowcasting exercise, the goal is to obtain an early estimate of current quarter GDP growth. Therefore timely releases of real economic activity are of great importance. In general, soft data is not subject to long publication delays and has proven to be useful for nowcasting US GDP growth in real time (Lahiri & Monokroussos, 2013). However, data that is released closer to the reference period tends to be less accurate (Bok et al., 2018). Therefore the data set contains soft data and hard data to combine early signals and more accurate estimates. The monthly release dates of the variables can be decomposed into 12 blocks, denoted ν_1 - ν_{12} and are displayed in Table 1.

Table 1: Monthly release dates

ν_1	ν_2	ν_3	ν_4
1st Business day	3rd Business day	1st Wednesday of the month	1st Friday of the month
ν_5	ν_6	ν_7	ν_8
9th Business day	15th of month	3rd Thursday of month	12th Business day
ν_9	ν_{10}	ν_{11}	ν_{12}
17th Business day	2nd Week of month	3rd week of month	Last week of month

The 36 variables reflect the headline releases of the most important macroeconomic indicators, those that "move markets and make front page news" (Bok et al., 2018). Table 2 lists the variables, which are grouped into eight categories: labor, surveys, manufacturing, housing and construction, international trade, income, retail and consumption and others. Column 3 and 4 of Table 2 reports the corresponding release the variable belongs and the timing of the release within a quarter.

Table 2: Macroeconomic data releases

Variable	**Category**	**Release**	**Timing**
All employees: Total nonfarm	L	Employment Situation	ν_4, one month prior
Real gross domestic product	O	Gross Domestic Product	ν_{12}, prior quarter
ISM mfg.: PMI composite index	S	ISM Manufacturing Report on Business	ν_1, one month prior
CPI-U: All items	O	Consumer Price Index	ν_7, one month prior
Manufacturers new orders: Durable goods	M	Manufacturers' Shipments, Inventories, and Orders	ν_1, two months prior
Retail sales and food services	R & C	Retail Trade	ν_5, one month prior
New single family houses sold	H & C	New Residential Sales	ν_9, one month prior
Housing starts	H & C	New Residential Constructions	ν_8, one month prior
Civilian unemployment rate	L	Employment Situation	ν_4, one month prior
Industrial production index	M	Industrial Production and Capacity Utilization	ν_7, one month prior
PPI: Final Demand	O	Producer Price Index	ν_7, one month prior
ADP nonfarm private payroll employment	L	ADP National Employment Report	ν_3, one month prior
Empire State Mfg. Survey: General business conditions	S	Empire State Manufacturing Survey	ν_7, current month
Merchant wholesalers: Inventories: Total	M	Wholesale Trade	ν_7, two months prior
Value of construction put in place	H & C	Construction Spending	ν_1, two months prior
Philly Fed Mfg. business outlook: Current activity	S	Manufacturing Business Outlook Survey	ν_{10}, current month
Import price index	T	U.S. Import and Export Price Indexes	ν_7, one month prior
ISM nonmanufacturing: NMI composite index	S	ISM Non-Manufacturing Report on Business	ν_2, one month prior
ISM mfg.: Prices index	S	ISM Manufacturing Report on Business	ν_1, one month prior
Building permits	H & C	New Residential Constructions	ν_8, one month prior
Capacity utilization	M	Industrial Production and Capacity Utilization	$\nu 7$, one month prior
PCE less food and energy: Chain price index	O	Personal Income and Outlays	ν_{12}, one month prior
CPI-U: All items less food and energy	O	Consumer Price Index	ν_7, one month prior
Inventories: Total business	M	Manufacturing and Trade Inventories	ν_6, two months prior
Nonfarm business sector: Unit labor cost	L	Productivity and Costs	ν_1, prior quarter
JOLTS: Job openings: Total	L	Job Openings and Labor Turnover	ν_6, two months prior
Real personal consumption expenditures	R & C	Personal Income and Outlays	ν_{12}, one month prior
PCE: Chain price index	O	Personal Income and Outlays	ν_{12}, one month prior

ISM mfg: Employment index	S	ISM Manufacturing Report on Business	ν_1, one month prior
Export Price Index	T	U.S. Import and Export Price Indexes	ν_7, one month prior
Manufacturers shipments: Durable Goods	M	Manufacturers' Shipments, Inventories, and Orders	ν_1, two months prior
Mfrs unfilled orders: All manufacturers industries	M	Manufacturers' Shipments, Inventories, and Orders	ν_1, two months prior
Manufacturers inventories: Durable goods	M	Manufacturers' Shipments, Inventories, and Orders	ν_1, two months prior
Real gross domestic income	O	Gross Domestic Product	ν_{12}, prior quarter
Real disposable personal income	I	Personal Income and Outlays	ν_{12}, one month prior
Exports: Goods and services	T	U.S. International Trade in Goods and Services	ν_5, two months prior
Imports: Goods and services	T	U.S. International Trade in Goods and Services	ν_5, two months prior

Categories in abbreviation: **L** = Labor, **S** = Surveys, **M** = Manufacturing, **H &C** = Housing and Construction, **T** = International Trade, **I** = Income, **R&C** = Retail and Consumption, **O** = Others. Timing $\nu_1 - \nu_{12}$ corresponds to monthly release dates stated in Table 1. ν in descending order: ν_1 earliest release in given month, ν_{12} latest release, respectively.

The data set is a rich of macroeconomic information, but does not include financial data. Financial data - similarly to survey data - is not subject to long publication delays and hence can add timely information (Bańbura & Rünstler, 2011). However, the high volatility of financial variables introduces additional noise and therefore they are not included in the data set.

In order to estimate GDP growth in real time, I create a 'pseudo' real time data set. This data set replicates the information set that would have been available to the researcher at each specific time and imitates the data flow during the quarter. However, the data set is final, meaning that it does not take data revisions into account, hence 'pseudo' real time. The 'pseudo' real time data set ranges from 1980-01-01 to 2018-03-31, resulting in over 12400 observations. Most of the series are available on a monthly basis, only GDP, Gross Domestic Income (GDI) and "Nonfarm business sector: Unit labor cost" are released quarterly. The time series need to enter the model in stationary form, which in some cases requires a transformation of the variables. Table 7 in the Appendix gives a detailed description of the transformation of the variables. To test stationarity, an Augmented Dickey Fuller test was conducted, which showed that transformed variables are stationary.

4 Empirical Study

In the empirical study I evaluate the real time performance of the nowcasting models for the period of 2000Q1 - 2017Q4. In each quarter, the model parameters are estimated using the recent 15 years of data. The nowcasts are updated weekly. The updating period of the nowcasts in a given quarter starts one month before the reference quarter and ends one month after the quarter, when the BEA releases the advance GDP estimate, resulting in 22 nowcasts per quarter. The period consists of 72 quarters, therefore, a total of 1584 nowcasts are made per model. To assess the performance, the weekly nowcast is compared with the true GDP growth for the reference quarter. Lets denote the nowcast with n_t, where the subscript $t \in (1, \ldots, 22)$ indicates the week of the updating period the nowcast is made, and the real GDP growth is denoted as GDP, then the error is measured as:

$$ERROR_t = |n_t - GDP| \qquad\qquad \text{for } t \in (1, \ldots, 22).$$

In theory, the error should decrease during a given quarter, as more information becomes available. To examine the competing models, I first look at the absolute errors of the models. Subsequently, the models are compared relative to the benchmark model: DFM. The choice of the benchmark model is based on the fact that the DFM has proven to be an accurate tool in nowcasting GDP growth and is hence hard to beat. First, the models are compared on the whole sample 2000Q1 - 2017Q4 and subsequently on the period before the Great Recession (2000Q1 - 2007Q3) and after (2007Q4 - 2017Q4).

4.1 Results

Table 3 reports the average error per week and the corresponding significance level of Diebold Mariano test in the updating period for all nowcasting models over the three time spans 2000Q1 - 2017Q4, 2000Q1 - 2007Q3 and 2007Q4 - 2017Q4. The last row of Table 3 reports the average absolute error over the updating period, bold faced are the lowest errors, indicating that RP and LASSO yield the best results in nowcasting GDP growth in real time. Considering the whole period and 2007Q4 - 2017Q4, LASSO performs best with an average absolute error of 0.0172 and 0.0179 respectively, while RP does best in the period before the Great Recession with 0.0160.

Inspecting Table 3, two things should be noticed. First the period 2000Q1 - 2007Q3 exhibits lower errors than the period 2007Q4 - 2017Q4, which is not surprising, as this period includes the Great Recession, in which all models highly overestimated GDP growth. Second, the table exhibits the theoretical finding that an increasing information set increases the accuracy, which is reflected in the decreasing errors by week.

However, in all three time spans, RP and LASSO have errors of the similar magnitude, setting them apart from the other models. Especially in the period 2000Q1 - 2007Q3 the gap between the RP and LASSO and the remaining models is on average quite large. However, looking at the updating period in detail, I find that the gap between the models converges to the end of the updating period. In week 1 the difference between best and worst performing model equals to 0.0058 (2000Q1 - 2017Q4), 0.0066 (2000Q1 - 2007Q3), 0.0054 (2007Q4 - 2017Q4) and in the last week 0.0033 (2000Q1 - 2017Q4), 0.0036 (2000Q1 - 2007Q3), 0.0030 (2007Q4 - 2017Q4).

Moreover, I find that the DFM is the model that improved most over the updating period, whereas RP remained most constant in all considered periods: the error from week 1 compared to week 22 decreased by 0.0096 (2000Q1 - 2017Q4), 0.0080 (2000Q1 - 2007Q3) and 0.0110 (2007Q4 - 2017Q4) for DFM, while only 0.0057 (2000Q1 - 2017Q4), 0.0041

(2000Q1 - 2007Q3) and 0.0071 (2007Q4 - 2017Q4) for RP. Lastly, UFAMIDAS produces more accurate nowcasts than FAMIDAS in nearly all updating weeks in all periods.

To further elaborate on the accuracy of the nowcasting models, Figure 1 plots the error distribution and the accompanied 60% confidence interval for two subgroups: first quarter estimation are displayed in blue, estimation error for quarter 2,3 and 4 in red. The reason to divide the errors in two subgroups is motivated by the residual seasonality of GDP growth in the first quarter. The BEA found that even after adjusting for seasonality in the components of GDP, the first quarter GDP growth is substantially lower than of the other quarters. Therefore, economists cant argue if the published GDP growth value in first quarters actually reflects the real economic activity or if the number is undervalued.

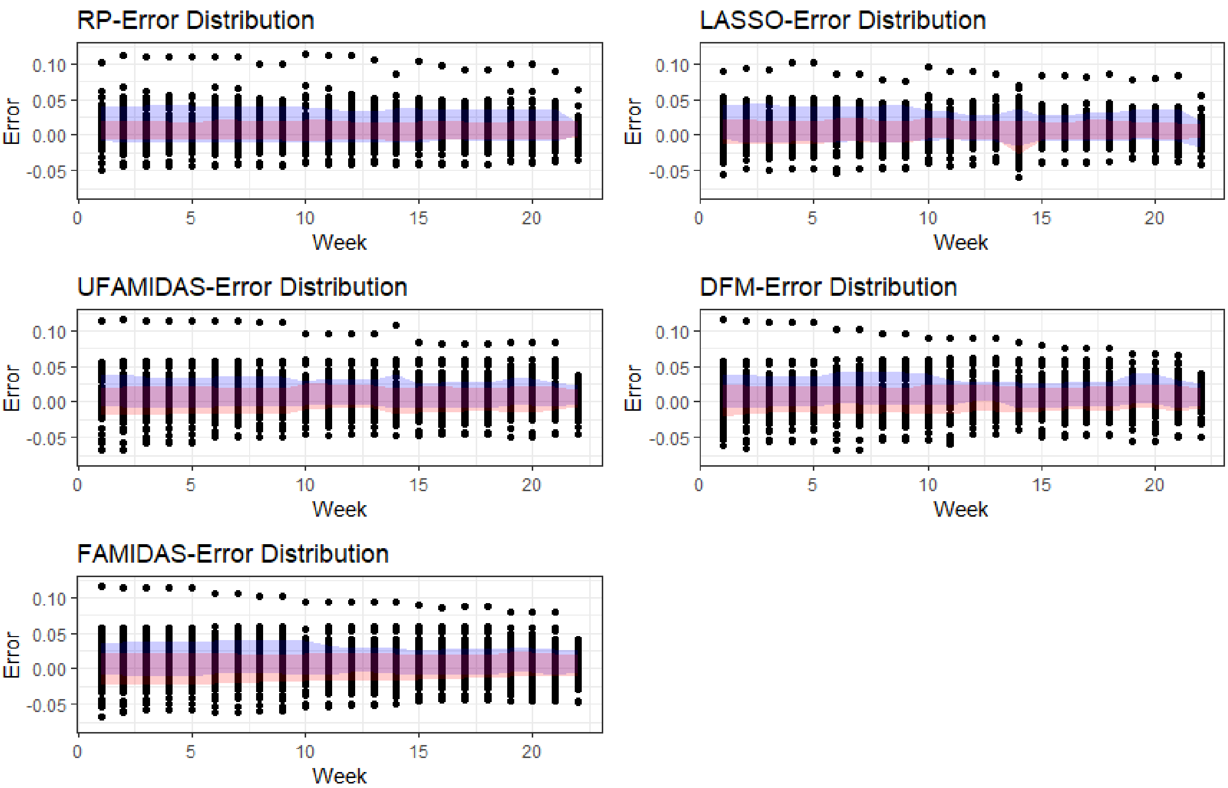

Figure 1: Error distributions over the period 2000Q1 - 2017Q4. The dots refer to the errors made in the respective week of the updating period in the quarters of the evaluation sample. The two colored 60% confidence bands correspond to two groups: the blue one indicates the errors made in first quarters, while the red one belongs to the other quarters.

In all five models, the blue band representing the errors in the first quarter is broader and upward biased, which is in line with residual seasonality.
The models exhibit some extreme errors in each updating week, these correspond exclusively to the 4th quarter 2008, in which GDP growth was equal to -8.4%. All nowcasting models highly overestimated real economic activity in this shock scenario. However, due to these extreme errors the plots are hard to read and therefore, Figure 10 in the Appendix

Table 3: Average absolute error in updating period

	2000Q1 - 2017Q4					2000Q1 -2007Q3					2007Q4 - 2017Q4				
Week	RP	LASSO	UFAMIDAS	DFM	FAMIDAS	RP	LASSO	UFAMIDAS	DFM	FAMIDAS	RP	LASSO	UFAMIDAS	DFM	FAMIDAS
1	0.0181(*)	0.0194(*)	0.0225	0.0239	0.0231	0.0162(*)	0.0178(*)	0.0208	0.0228	0.0207	0.0196(*)	0.0207(*)	0.0240	0.0248	0.0251
2	0.0182(*)	0.0190(*)	0.0232	0.0229	0.0234	0.0167(*)	0.0172(*)	0.0226	0.0222	0.0217	0.0194(*)	0.0205(**)	0.0237	0.0235	0.0248(**)
3	0.0179(*)	0.0184(*)	0.0224	0.0220	0.0232	0.0167(*)	0.0176(*)	0.0217	0.0214	0.0218	0.0190(**)	0.0192(**)	0.0230	0.0225	0.0243(**)
4	0.0179(*)	0.0184(*)	0.0222	0.0218	0.0231	0.0171(*)	0.0180(**)	0.0216	0.0213	0.0218	0.0186(*)	0.0187(*)	0.0227	0.0222	0.0242(*)
5	0.0179(*)	0.0183(*)	0.0220	0.0215	0.0230(**)	0.0172(**)	0.0178(*)	0.0215	0.0211	0.0217	0.0185(*)	0.0187(*)	0.0225	0.0219	0.0240(*)
6	0.0187(*)	0.0197	0.0213	0.0216	0.0224	0.0172(*)	0.0189	0.0211(**)	0.0237	0.0228	0.0199	0.0204	0.0215(**)	0.0198	0.0222(*)
7	0.0185	0.0193	0.0211	0.0212	0.0223	0.0170(**)	0.0186	0.0208	0.0228	0.0225	0.0198	0.0199	0.0214(**)	0.0198	0.0221(*)
8	0.0179(**)	0.0184	0.0205	0.0197	0.0220(*)	0.0164	0.0180	0.0195	0.0200	0.0220	0.0193	0.0188	0.0213(**)	0.0196	0.0220(**)
9	0.0175(**)	0.0182	0.0204	0.0197	0.0219(*)	0.0164	0.0179	0.0195	0.0199	0.0220(**)	0.0184	0.0185	0.0213(**)	0.0196	0.0219(**)
10	0.0183	0.0178(**)	0.0189	0.0207	0.0209	0.0162(**)	0.0161(*)	0.0185(**)	0.0223	0.0218	0.0202	0.0192	0.0192	0.0194	0.0202
11	0.0179	0.0168(*)	0.0190	0.0209	0.0208	0.0161(**)	0.0156(*)	0.0179(**)	0.0224	0.0215	0.0195	0.0178	0.0198	0.0197	0.0203
12	0.0171	0.0163(**)	0.0186	0.0191	0.0205	0.0155	0.0155	0.0177	0.0186	0.0208	0.0185	0.0170	0.0194	0.0195	0.0202
13	0.0167	0.0163(**)	0.0186	0.0190	0.0205(**)	0.0153	0.0154	0.0177	0.0186	0.0208	0.0179	0.0170	0.0194	0.0194	0.0202
14	0.0171	0.0224(**)	0.0200	0.0191	0.0199	0.0165	0.0222	0.0186	0.0189	0.0197	0.0176	0.0226	0.0212(**)	0.0192	0.0202
15	0.0172	0.0158(**)	0.0182	0.0181	0.0188	0.0158	0.0147	0.0175	0.0179	0.0184	0.0184	0.0168	0.0188	0.0183	0.0192
16	0.0171	0.0154(**)	0.0180	0.0178	0.0189	0.0156	0.0149	0.0173	0.0175	0.0185	0.0184	0.0158	0.0185	0.0180	0.0191
17	0.0162	0.0155(*)	0.0181	0.0178	0.0189	0.0153	0.0153	0.0177	0.0177	0.0186	0.0169	0.0157	0.0185	0.0180	0.0191
18	0.0163	0.0156(**)	0.0181	0.0178	0.0188	0.0155	0.0153	0.0179	0.0179	0.0186	0.0171	0.0159	0.0183	0.0178	0.0190
19	0.0172	0.0155(**)	0.0174	0.0185	0.0186	0.0156(*)	0.0137(*)	0.0184(**)	0.0208	0.0193	0.0186	0.0171	0.0167	0.0165	0.0181(*)
20	0.0175	0.0154(*)	0.0176	0.0189	0.0187	0.0161(*)	0.0137(*)	0.0187(*)	0.0217	0.0194(*)	0.0186(*)	0.0168	0.0167	0.0165	0.0181(*)
21	0.0164	0.0147(*)	0.0173	0.0182	0.0183	0.0150(*)	0.0140(*)	0.0177(**)	0.0195	0.0187	0.0175	0.0153	0.0171	0.0171	0.0181
22	0.0124(*)	0.0115(*)	0.0135	0.0143	0.0148	0.0121	0.0119	0.0136	0.0149	0.0155	0.0126	0.0112	0.0134	0.0138	0.0142
AVG	0.0173(*)	**0.0172**(*)	0.0195(**)	0.0197	0.2060(*)	**0.0160**(*)	0.0164(*)	0.0190(*)	0.0202	0.0204	0.0184(*)	**0.0179**(*)	0.0199(**)	0.0194	0.0207(*)

Updating period week 1 corresponds to first nowcast one month prior to reference quarter and week 22 to last nowcast, one month after the reference quarter,when the BEA releases the advance GDP estimate. Errors measured as difference of nowcast made in real time and actual GDP growth in the reference quarter. Bold faced values in last row correspond to lowest absolute error over updating period. In brackets significance level of Diebold Mariano test against benchmark model DFM: (*) corresponds to p-value < 0.05, (**) corresponds to p-value < 0.10

plots the error distribution of the models excluding 2008Q4. Additional to the upward bias, the LASSO error distribution has an uncommon feature: first quarter errors in week 14 are upward biased, while the other errors are downward biased, visualized through the upward spike and downward spike, respectively. The UFAMIDAS exhibits the same feature, but not as distinctively. Inspecting the red bands, I find good forecasting features, errors are close to symmetrically distributed around zero and narrow to the end of the updating period. Only for the LASSO and RP a minor upward bias is visible.
Next, I compare the performance of the models relative to the benchmark model, DFM. Table 4 reports the errors relative to the DFM for all weeks in the updating period in all considered periods. A value below 1.0 indicates that the model outperforms the benchmark and above 1.0 that the benchmark is more accurate. The last row of the table presents the average relative errors. Bold faced are the lowest average values for the respective periods. Over the entire time span and 2007Q4 - 2017Q4, LASSO performed best with an average relative error of 0.87 and 0.92, while in the period before the Great Recession, RP yielded the best result with 0.80. In all considered periods FAMIDAS did not beat the benchmark on average.
Moreover, I find that the results before and after the Great Recession differ quite a bit. UFAMIDAS outperforms the benchmark in the period before the Great Recession with 0.95, whereas it is not able to beat the benchmark in 2007Q4 - 2017Q4, with an average relative error of 1.03. In the period of 2000Q1 - 2007Q3, the models RP and LASSO yield good results with relative errors of 0.80 and 0.82. Inspecting the period 2007Q4 - 2017Q4, I find that the performances of the models are more similar to that of the benchmark, with RP and LASSO having average relative errors of 0.95 and 0.92, respectively. RP and LASSO are superior over DFM in terms of nowcasting accuracy before the Great Recession, but in the period 2007Q4 - 2017Q4, the performance is comparable to the DFM.
Considering the whole sample 2000Q1 - 2017Q4, only RP is consistently able to outperform the benchmark. Especially in the early weeks of the updating period, RP produces accurate nowcasts. The LASSO outperforms the DFM in 21 out of 22 cases: only in week 14, the relative error is above 1.0 with its value being 1.17. This might be caused by the uncommon feature of the error distribution described above. However, I find that towards the end of the updating period (weeks 15 to 22), LASSO performs better than the RP approach. UFAMIDAS performs better than the benchmark in 10 out of 22 cases, but still has an average error slightly below 1.0. FAMIDAS can only beat the benchmark in 2 cases, yielding an average relative error of 1.04. Inspecting the time span before the Great Recession in more detail, I find similar results as for the period 2000Q1 - 2017Q4, only with slightly different numbers. The period 2007Q4 - 2017Q4 yields different results and needs special attention. RP and LASSO are only able to beat the benchmark in 14 and 17 cases respectively. UFAMIDAS, in contrast to the other periods, is only outperforming the DFM in three cases.

To get an intuition of the models and the differences between the models, Figure 2 plots the evolution of the nowcasts in the updating period of 2017Q4.

Table 4: Errors relative to bechmark DFM in updating period

Week	**2000Q1 - 2017Q4**					**2000Q1 - 2007Q3**					**2007Q4 - 2017Q4**				
	RP	LASSO	UFAMIDAS	DFM	FAMIDAS	RP	LASSO	UFAMIDAS	DFM	FAMIDAS	RP	LASSO	UFAMIDAS	DFM	FAMIDAS
1	0.76	0.81	0.94	1	0.97	0.71	0.78	0.91	1	0.91	0.79	0.83	0.97	1	1.01
2	0.79	0.83	1.01	1	1.02	0.75	0.78	1.02	1	0.98	0.82	0.87	1.01	1	1.05
3	0.82	0.84	1.02	1	1.05	0.78	0.82	1.01	1	1.02	0.85	0.85	1.02	1	1.08
4	0.82	0.84	1.02	1	1.06	0.80	0.85	1.01	1	1.02	0.84	0.84	1.02	1	1.09
5	0.83	0.85	1.02	1	1.07	0.81	0.84	1.02	1	1.03	0.85	0.85	1.03	1	1.10
6	0.86	0.91	0.99	1	1.04	0.73	0.80	0.89	1	0.96	1.00	1.03	1.08	1	1.12
7	0.87	0.91	1.00	1	1.05	0.75	0.82	0.91	1	0.99	1.00	1.01	1.08	1	1.12
8	0.91	0.93	1.04	1	1.11	0.82	0.90	0.98	1	1.10	0.99	0.96	1.09	1	1.12
9	0.89	0.93	1.04	1	1.11	0.83	0.90	0.98	1	1.11	0.94	0.94	1.09	1	1.12
10	0.88	0.86	0.91	1	1.01	0.72	0.72	0.83	1	0.98	1.04	0.99	0.99	1	1.04
11	0.86	0.80	0.91	1	1.00	0.72	0.69	0.80	1	0.96	0.99	0.91	1.01	1	1.03
12	0.90	0.85	0.98	1	1.07	0.83	0.84	0.95	1	1.12	0.95	0.87	1.00	1	1.03
13	0.88	0.86	0.98	1	1.07	0.82	0.83	0.95	1	1.12	0.92	0.88	1.00	1	1.04
14	0.90	1.17	1.05	1	1.05	0.88	1.18	0.99	1	1.04	0.91	1.17	1.10	1	1.05
15	0.95	0.87	1.00	1	1.04	0.89	0.82	0.98	1	1.03	1.00	0.92	1.02	1	1.05
16	0.96	0.86	1.01	1	1.06	0.89	0.85	0.99	1	1.06	1.02	0.88	1.03	1	1.06
17	0.91	0.87	1.02	1	1.06	0.87	0.87	1.00	1	1.05	0.94	0.87	1.03	1	1.06
18	0.92	0.88	1.02	1	1.06	0.87	0.85	1.00	1	1.04	0.96	0.89	1.03	1	1.07
19	0.93	0.84	0.95	1	1.01	0.75	0.66	0.88	1	0.93	1.13	1.04	1.01	1	1.10
20	0.93	0.82	0.93	1	0.99	0.74	0.63	0.86	1	0.89	1.13	1.02	1.01	1	1.09
21	0.90	0.81	0.95	1	1.01	0.77	0.72	0.91	1	0.96	1.02	0.89	1.00	1	1.06
22	0.87	0.81	0.94	1	1.04	0.81	0.80	0.91	1	1.04	0.91	0.81	0.97	1	1.03
Avg	0.88	**0.87**	0.99	1	1.04	**0.80**	0.82	0.95	1	1.01	0.95	**0.92**	1.03	1	1.07

Updating period week 1 corresponds to first nowcast one month prior to reference quarter and week 22 to last nowcast, one month after the reference quarter,when the BEA releases the advance GDP estimate. Relative errors measured as ratio of error made by respective model to DFM. Bold faced values in last row correspond to lowest relative error in the updating period.

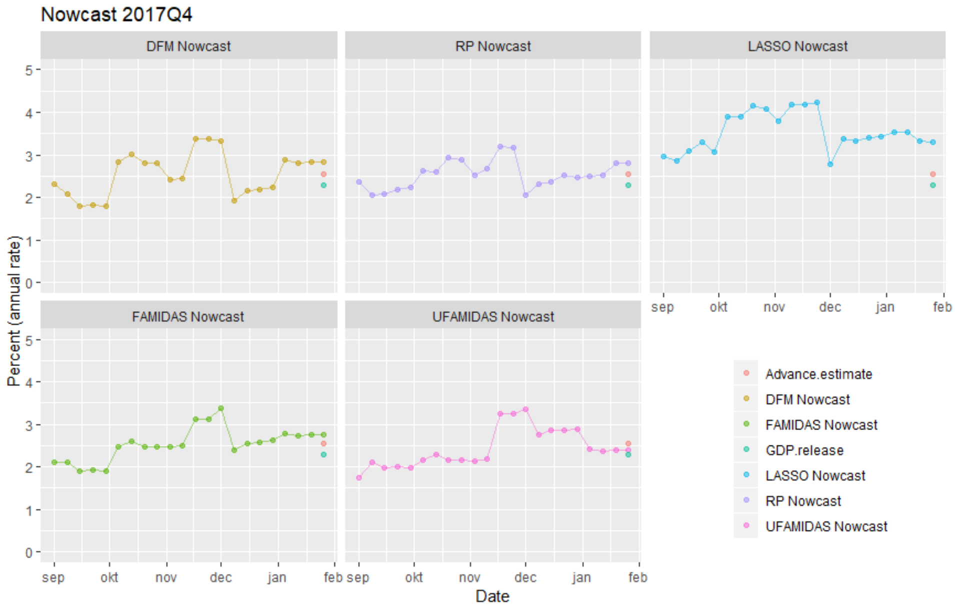

Figure 2: Nowcast evolution in updating period 2017Q4

Figure 2 shows the evolution in one specific updating period and the accuracy of the models should not be mistaken with the general accuracy. Consider for example LASSO: even though it yields together with RP the best results, in the updating period of 2017Q4, its final nowcast highly overestimates real GDP growth in the quarter. This might be caused by the initial nowcast of LASSO: where the other models' first estimate of GDP growth is around 2%, LASSOs' is at 3%. In each model, we see an increase in the estimates around mid-November followed by a drop in the beginning of December. Interestingly, the models that are based on latent factors decrease one week later, in the second week of December. The fact that data realeases are summarized in a factor could have caused the "delay". A first spike in the evolution of the nowcasts is already visible in the beginning of October, which is hardly noticeable for UFAMIDAS. DFM, FAMIDAS and RP exhibit two clear increases in the nowcast, while UFAMIDAS increases rapidly only in mid-November and LASSO already in October but does only decrease slightly until it drops in December. All final nowcasts overestimate real GDP growth for that quarter, only UFAMDIAS's final nowcast is below the BEA advance estimate.

The red bands in Figure 1 already suggest a slight upward bias in the nowcasts, especially in week 22. To exemplify this argument, Figure 3 displays the nowcast evolution with the accompanied nowcast uncertainty in the updating period 2017Q4.

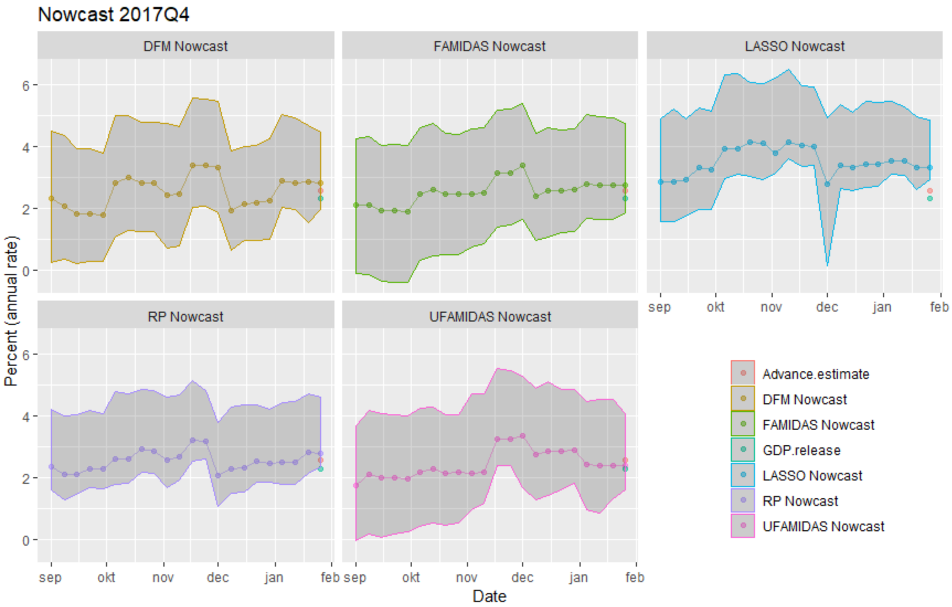

Figure 3: Nowcast evolution in updating period 2017Q4 accompanied by 60% nowcast uncertainty

Especially LASSO exhibits this feature, where the nowcast uncertainty band in week 22 does not even include the real GDP growth value. It suggests that residual seasonality is not only existent in first quarter GDP growth. However, to compare upward bias to the first quarter one, Figure 4 plots the nowcasting evolution in the updating period 2017Q1 and the accompanied uncertainty.

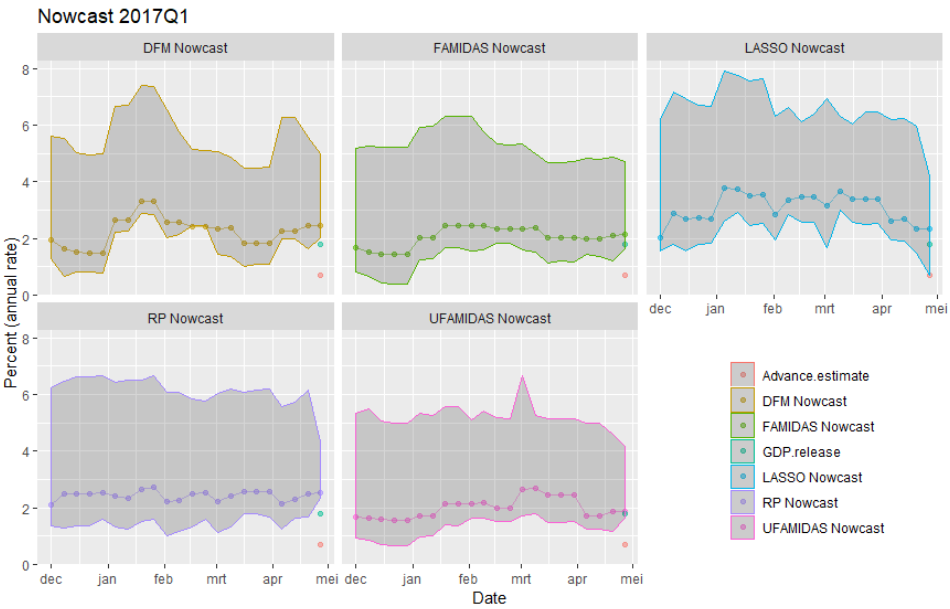

Figure 4: Nowcast evolution in updating period 2017Q1 accompanied by 60% nowcast uncertainty

The nowcasts in Figure 4 exhibit the extreme upward bias discussed earlier. Also the upward spike in week 14 for Q1 and downward spike for the other quarters for the LASSO approach, as displayed in Figure 1, are visible in Figure 4 (in the beginning of March) and in Figure 3 (in the beginning of December), respectively.

In the following, I discuss the results for the nowcasting models in more detail. First, I focus on the models that use a common factor to describe the co-movement of the macroeconomic variables. Figure 5 displays the evolution of the common factor over the considered period 2000Q1- 2017Q4.

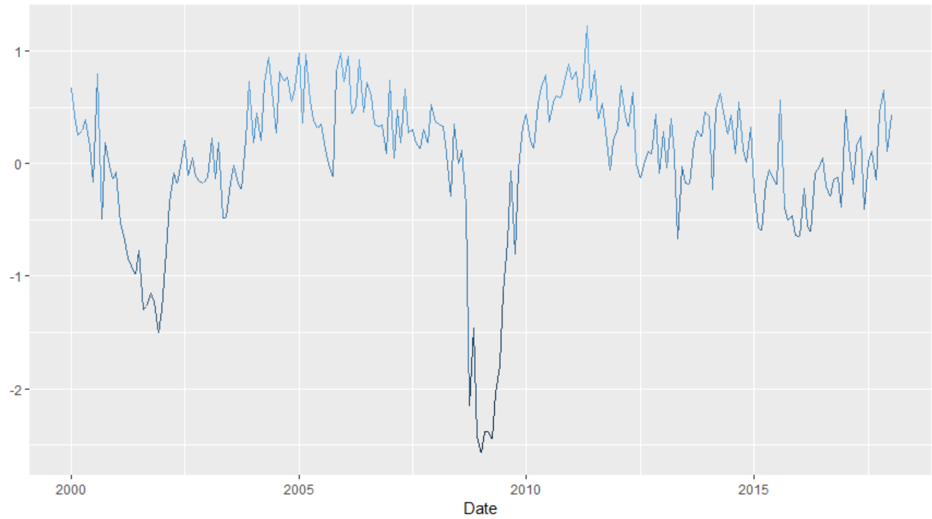

Figure 5: Evolution of common factor over 2000Q1 - 2017Q4

The two recessions in that period are clearly visible, the early 2000s recession and the Great Recession, in which the common factor hit the lowest level of -1.5 in October 2001 and -2.5 in January 2009, respectively. The three approaches DFM, UFAMIDAS and FAMIDAS only differ in the way the nowcast is obtained, but not in the factor estimation. In the DFM case, the nowcast is computed by an OLS regression (see Equation 7). To investigate what drives the nowcast in the updating period Figure 6 plots the average coefficient evolution in the updating period.

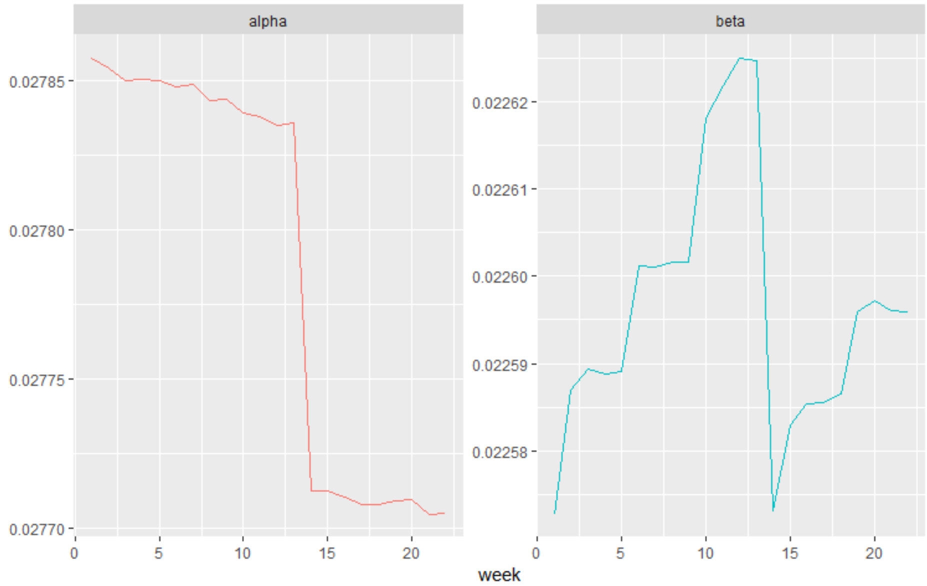

Figure 6: Average DFM regression coeffcients in updating period

In week 14 both the intercept and the beta coefficient drop. This week corresponds to the last week of the quarter, in which various macroeconomic indicators are released. That suggests that the releases in the final week of the quarter drive the nowcast down and the DFM nowcast “overestimated” GDP growth in the weeks before. However, this still need to be treated with caution, as the drop in coefficients is of the magnitude of 0.0001 for alpha and 0.00004 for beta, respectively. A different picture can be drawn by inspecting the evolution of the coefficients over time, displayed in Figure 7.

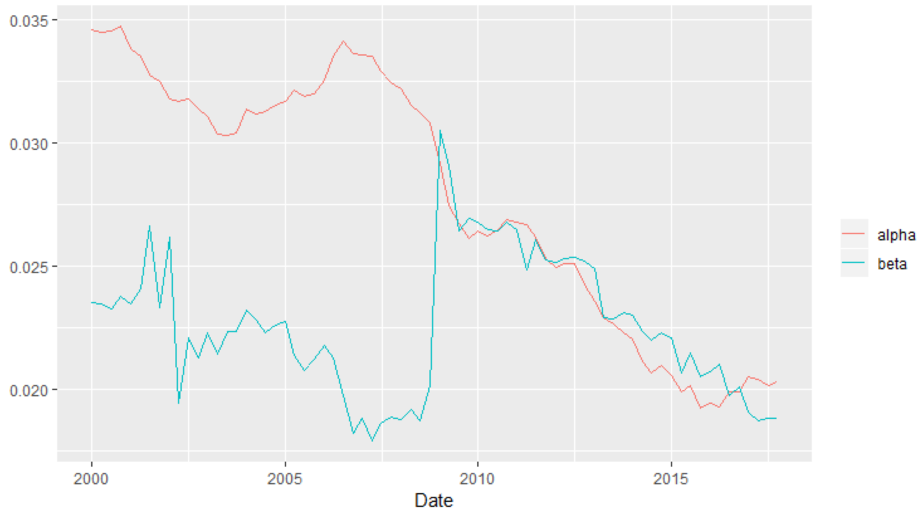

Figure 7: Average DFM regression coefficients over period 2000Q1 - 2017Q4

Three things can be noticed, (i) the intercept decreases towards the end of the period, (ii) during the two recessions the beta coefficient is highly volatile and (iii) after the Great Recession alpha and beta evolve jointly. A reason for the co-movement of the coefficients after the financial crisis is the stable development of the US economy. The US economy is about to be in the longest uninterrupted expansion in its history.
In the UFAMIDAS approach also lags of the factor are considered in the regression. The average regression coefficients of the UFAMDIAS approach (Equation 10) are plotted in Figure 8.

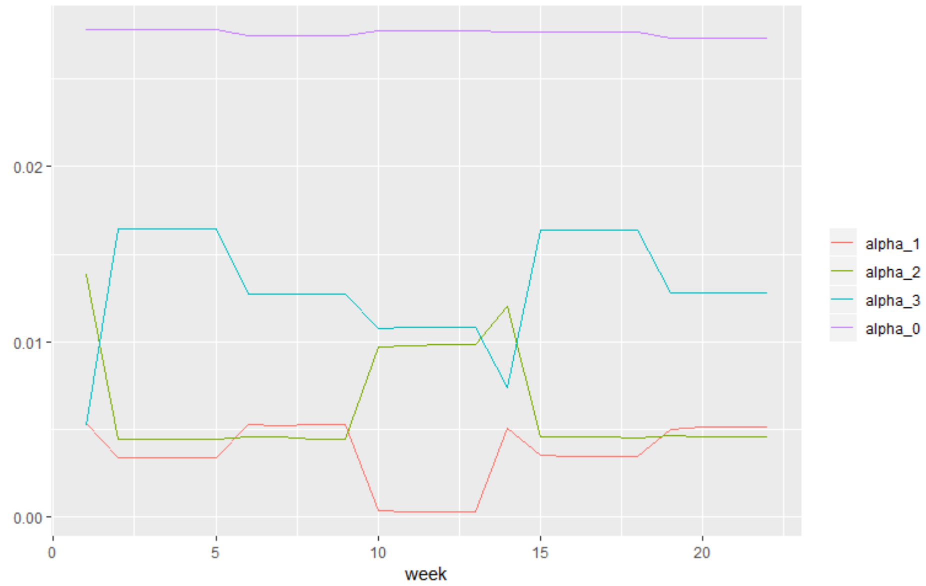

Figure 8: Average UFAMIDAS regression coefficients in updating period

I can not draw a broad conclusion on the UFAMIDAS nowcast behaviour based on the average regression coefficients. However, again at the end of quarter (week 14 to 15) jumps in the average coefficients are visible. The intercept on the other hand does not change substantially throughout the updating period. Considering the average coefficients over the period 2000Q1 - 2017Q4, displayed in Figure 9, differences to the DFM approach are to be noticed.

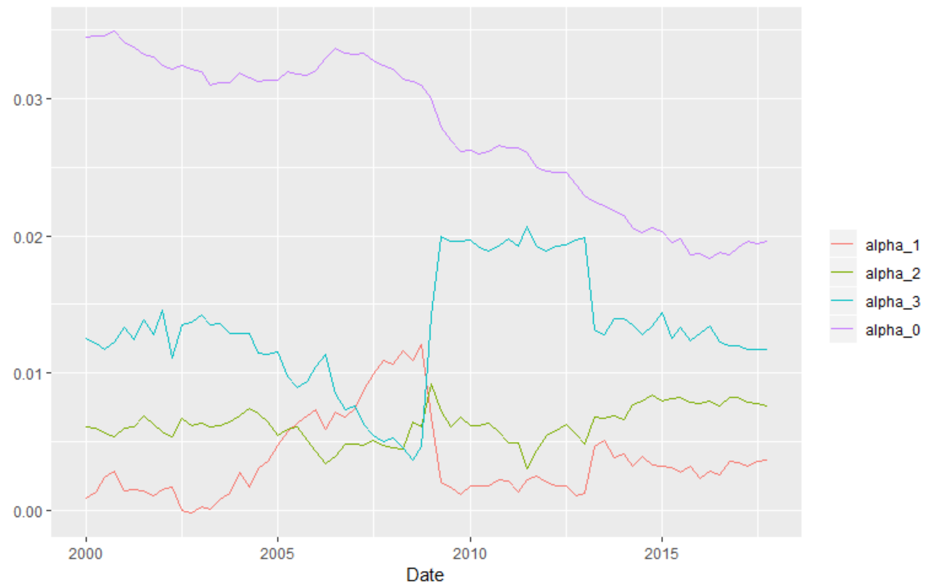

Figure 9: Average UFAMIDAS regression coefficients over 2000Q1 - 2017Q4

Similar to the DFM approach, in the beginning of the period the coefficient corresponding to the common factor alpha 1,2 and 3 are far off from the intercept. However, the volatile evolution in the recession times is not identifiable. In the financial crisis the 3rd lag of the common factor dominated the GDP growth nowcast, while the alpha 1 dropped. After the economy had recovered from the financial crisis the 3 coefficients move similarly, but not in the same magnitude as the intercept.
The worst performing model using a common factor FAMIDAS employs an Almon lag polynomial, which maximum order lag K is selected bases on the Akaike Information Criterion. Table 5 reports the average coefficients (see Equation 9) and maximum lag selected in period 2000Q1 - 2017Q4.

Table 5: Average FAMIDAS coefficients over period 2000Q1 - 2017Q4

β_0	β_1	θ_1	θ_2	K
0.0342	0.0269	0.9564	0.0839	3.0890

The next model I shed light on is the RP approach. This model reduction technique produces a subspace of the regressorspace (36 indicators) where $p \ll 36$. Unfortunately, there is no information criterion to select the optimal value of p in terms of nowcasting accuracy. Therefore, I estimate the nowcast error for several values of $p \in (1, \ldots, 5)$ and select the model that yields the lowest nowcasting error, which is in fact the case when p is equal to 5. However, as for each nowcast, there are 1000 random projection regressions estimated, this approach is computationally intensive. The state of the economy does not change within seconds, minutes or even hours, so, especially since this nowcasting exercise is made in a weekly setting, the computational burden can be neglected.
Lastly I discuss the only approach that does not compress the data, but rather selects informative predictors - the LASSO. In the updating period 2017Q4, displayed in Figure 2, the LASSO selects an average of 10 indicators, mostly including Total Nonfarm Payroll, PMI Composite Index, Unemployment Rate, Capacity Utilization and main indicators on manufacturing, trade and surveys. This example shows that a variety of soft and hard data, covering sectors of manufacturing, labor, trade, housing and construction, as well as surveys, is included in the model. To further elaborate on this argument, Table 6 shows the variables and number of times it has been selected as a predictor in a nowcast over the period 2000Q1 - 2017Q4.

Two variables have been selected in over 85% of all nowcasts: "Total Nonfarm Payroll" and "ISM mfg.: PMI composite index". Both indicators are important measures on the health of the economy, that are released timely and hence give an early intuition of the state of the economy. The Total Nonfarm Payroll measures the number of US workers in the economy and covers nearly 80% of all workers who contribute to the GDP. The Institute of Supply Management (ISM) releases data on surveys, completed by purchasing managers of more than 300 industrial companies, on their opinion of the economic outlook. Due to their timely releases, these indicators have explanatory power to nowcast GDP growth in real time, which is also reflected in the fact that the ISM non-manufacturing: NMI composite index and ISM Employment Index are selected in 43% of the cases and 30%, respectively. These findings are in line with those of Lahiri and Monokroussos (2013). In general, indicators corresponding to the group surveys have been selected most often, 3571 times exactly. Beside survey variables, also indicators belonging to manufacturing, international trade and labor have been selected numerous times. LASSO selected the variable Exports: Goods and Services in 73% of all nowcasts, compared to 51% for Imports: Goods

Table 6: Number of predictors being selected by LASSO in nowcasts over the period 2000Q1 - 2017Q4

Indicator			Indicator		
All employees: Total nonfarm	1379	(87%)	Real gross domestic income	342	(22%)
(Intercept)	1373	(87%)	Inventories: Total business	336	(21%)
ISM mfg.: PMI composite index	1344	(85%)	ISM mfg.: Prices index	321	(20%)
Exports: Goods and services	1151	(73%)	Capacity utilization	318	(20%)
Value of construction put in place	981	(62%)	CPI-U: All items	287	(18%)
PPI: Final Demand	241	(58%)*	Manufacturers inventories: Durable goods	271	(17%)
Imports: Goods and services	806	(51%)	Nonfarm business sector: Unit labor cost	248	(16%)
Merchant wholesalers: Inventories: Total	745	(47%)	Export Price Index	177	(11%)
Industrial production index	683	(43%)	Real personal consumption expenditures	98	(7%)*
ISM nonmanufacturing: NMI composite index	256	(43%)*	Manfacturers new orders: Durable goods	88	(6%)
Empire State Mfg. Survey: General business conditions	465	(40%)*	Building permits	84	(5%)
Import price index	610	(39%)	JOLTS: Job openings: Total	62	(5%)*
Manufacturers shipments: Durable Goods	533	(34%)	Retail sales and food services	70	(4%)
ISM mfg: Employment index	478	(30%)	Real gross domestic product	63	(4%)
Mfrs unfilled orders: All manufacturers industries	474	(30%)	PCE: Chain price index	62	(4%)
CPI-U: All items less food and energy	455	(29%)	PCE less food and energy: Chain price index	54	(3%)
Real disposable personal income	422	(27%)	Housing starts	48	(3%)
Civilian unemployment rate	416	(26%)	New single family houses sold	9	(1%)
Philly Fed Mfg. business outlook: Current activity	382	(24%)			

In brackets percentage of indicators selected in nowcasts. 31 out of 36 were available over the whole period 2000Q1 - 2017Q4, which corresponds to 1584 nowcasts. The 5 indicators, labeled with * are only available for a limited time period . PPI: Final Demand for 19Q (418 nowcasts), NMI Composite Index for 27Q (594 nowcasts), Empire State Mfg. Survey: General business conditions for 53Q (1166 nowcasts), Real personal consumption expenditures for 62Q (1364 nowcasts) and JOLTS: Job openings: Total for 54Q (1188 nowcasts).

and Services, even tough it accounted for less of the total GDP. In 2017, the US trade volume in imported goods and services was 2.9 trillion US Dollars relative to 2.3 Dollars in exports. In the category housing and construction I find that only one variable Value of Construction put in place is a good predictor (62%), whereas the others have been selected in less than 6% of the nowcasts. Moreover, the nowcasts included in 87% of the cases an intercept, indicating the basic trend. The consumer price index (CPI), which measures inflation, seems not to drive the nowcasts of GDP growth: the core component of CPI is selected in 29% of the nowcasts, while whole CPI only in 18%. This might be caused by the fact that in real time, inflation plays a minor role. In order to have a powerful set of predictors, it is important to include both timely and more accurate releases. The LASSO's ability to select informative predictors makes it a very suitable tool to nowcast GDP growth in real time.

5 Discussion & Conclusion

To conclude which econometric model nowcasts US GDP growth in real time most accurately, an extensive empirical study was conducted. Considering 72 quarters over the period 2000Q1 – 2017Q4, I find that the methods LASSO and random projection regression perform best. LASSO has been used only a few times in monitoring macroeconomic conditions and is a good alternative to the well-established models (Tiffin, 2016). Surprisingly well performed the random projections method, which provides accurate estimates of the current state of the economy. A drawback of this model is the computational burden, since a large number of random regressions need to be estimated to obtain a single nowcast. Monetary policy and business decisions are based on the assessment of the current state of the economy, which does not change within seconds, minutes or hours. Thus, the issue of the computational time can be neglected. However, in a fast-paced environment it is not a suitable tool. The two mentioned models performed well over the whole sample as well as over both subsamples 2000Q1 – 20007Q3 and 2007Q4 – 2017Q4. However, I cannot draw a conclusion which of the models is better suited to nowcast GDP growth in real time, especially since the random projection method delivers more accurate nowcasts in the first half of the updating period , while LASSO performs better towards the end. A possible solution would be to consider a nowcast combination of these two mentioned models.

The FAMIDAS capability to handle ragged edge data sets with indicators sampled at different frequencies makes it appealing in the context of nowcasting in real time. However, FAMIDAS performed worst in all considered periods. Moreover, the FAMIDAS approach is only able to beat the benchmark (DFM) in the period before the Great Recession in 9 out of 22 weeks in the updating period, but still on average is not able to beat the benchmark. A priori I expected the FAMIDAS approach to perform better, as it can be regarded as an extension of the DFM. The factor estimation is based on the same procedure as in the DFM case, but it exploits all factors and their lags; not only those factors when GDP is observed. This might be caused by the fact that the FAMIDAS approach employs an exponential lag polynomial, which bears the costs of the model becoming non-linear. FAMIDAS outperforms the unrestricted counterpart UFAMIDAS only in 1 out of 22 cases for two considered periods and 2 out of 22 in the period 2000Q1 – 2007Q3. Literature suggests that the unrestricted MIDAS approach is superior when the differences in sampling frequencies are not big, as is the case in macroeconomic application (Foroni, Marcellino, & Schumacher, 2015). Therefore, I believe that the MIDAS approach can still be useful in nowcasting, but rather in financial applications, when sampling frequencies vary from hourly to even

quarterly.
The UFAMIDAS can be regarded as extension of the DFM, as instead of a classic regression a MIDAS regression is applied to obtain the nowcast. However, I find that the UFAMIDAS is able to beat the benchmark (DFM) before the great recession, but not in the period 2007Q4 - 2017Q4. Considering the whole period the average relative error of UFAMIDAS is 0.99, suggesting that the advantages of the MIDAS regression are minor in nowcasting GDP growth.
Throughout the updating period the gap between the models converges. While in the beginning of the updating period RP and LASSO yield good results, towards the end the difference in error is rather small, suggesting that only RP and LASSO perform well with a small information set. Investigating the error distribution of the considered nowcasting models, I find that no model can handle residual seasonality in first quarter GDP. Additionally, an upward bias towards the end of the updating period is visible in all models for the other quarters as well.
Still, the results need to be inspected with caution as the pseudo real time data set was created using final data. I did not consider data revisions, since gathering non-revised data and data revisions would have been tough and beyond the scope of this thesis, especially as I conducted this extensive empirical analysis over 72 quarters. Nonetheless, the results do deliver a good picture of the accuracy of the presented models in real time. A possible extension of this research would be to investigate the data revision on the nowcasting performance in real time.
Additionally, there is still a lot of room for research about the random projection approach. For example, there has not been introduced a method to select the optimal value of p - the dimension of the low dimensional subspace. Furthermore, in order to decrease the computational time, one could research the number of random projection regression that are sufficient to obtain an accurate nowcast. If the accuracy converges fast the random projection approach might be also suited in financial applications.

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Appendix

Table 7: Transformation of variables to induce stationarity

Variable	Frequency	First Observation	Transformation
All employees: Total nonfarm	M	1/1/1980	first difference
Real gross domestic product	Q	1/1/1980	Log difference (Q)
ISM mfg.: PMI composite index	M	1/1/1980	
CPI-U: All items	M	1/1/1980	Log difference (M)
Manfacturers new orders: Durable goods	M	2/1/1992	Log difference (M)
Retail sales and food services	M	1/1/1992	Log difference (M)
New single family houses sold	M	1/1/1980	Log difference (M)
Housing starts	M	1/1/1980	Log difference (M)
Civilian unemployment rate	M	1/1/1980	Log difference (M)
Industrial production index	M	1/1/1980	Log difference (M)
PPI: Final Demand	M	11/1/2009	Log difference (M)
ADP nonfarm private payroll employment	M	4/1/2002	first difference
Empire State Mfg. Survey: General business conditions	M	7/1/2001	
Merchant wholesalers: Inventories: Total	M	1/1/1992	Log difference (M)
Value of construction put in place	M	1/1/1993	Log difference (M)
Philly Fed Mfg. business outlook: Current activity	M	1/1/1980	
Import price index	M	9/1/1982	Log difference (M)
ISM nonmanufacturing: NMI composite index	M	1/1/2008	
ISM mfg.: Prices index	M	1/1/1980	
Building permits	M	1/1/1980	first difference
Capacity utilization	M	1/1/1980	Log difference (M)
PCE less food and energy: Chain price index	M	1/1/1980	Log difference (M)
CPI-U: All items less food and energy	M	1/1/1980	Log difference (M)
Inventories: Total business	M	1/1/1992	Log difference (M)
Nonfarm business sector: Unit labor cost	Q	1/1/1980	Log difference (Q)
JOLTS: Job openings: Total	M	12/1/2000	first difference
Real personal consumption expenditures	M	1/1/1999	Log difference (M)
PCE: Chain price index	M	1/1/1980	Log difference (M)
ISM mfg: Employment index	M	1/1/1980	
Export Price Index	M	9/1/1983	Log difference (M)
Manufacturers shipments: Durable Goods	M	1/1/1992	Log difference (M)
Mfrs unfilled orders: All manufacturers industries	M	1/1/1992	Log difference (M)
Manufacturers inventories: Durable goods	M	1/1/1992	Log difference (M)
Real gross domestic income	Q	1/1/1980	Log difference (Q)
Real disposable personal income	M	1/1/1980	Log difference (M)
Exports: Goods and services	M	1/1/1992	Log difference (M)
Imports: Goods and services	M	1/1/1992	Log difference (M)

Table 8: Restriction on factor loading matrix in DFM

	G	S	R	L
All employees: Total nonfarm	1	0	0	1
Real gross domestic product	1	0	1	0
ISM mfg.: PMI composite index	1	1	0	0
CPI-U: All items	1	0	0	0
Manufacturers new orders: Durable goods	1	0	1	0
Retail sales and food services	1	0	1	0
New single family houses sold	1	0	1	0
Housing starts	1	0	1	0
Civilian unemployment rate	1	0	0	1
Industrial production index	1	0	1	0
PPI: Final Demand	1	0	0	0
ADP nonfarm private payroll employment	1	0	0	1
Empire State Mfg. Survey: General business conditions	1	1	0	0
Merchant wholesalers: Inventories: Total	1	0	1	0
Value of construction put in place	1	0	1	0
Philly Fed Mfg. business outlook: Current activity	1	1	0	0
Import price index	1	0	0	0
ISM nonmanufacturing: NMI composite index	1	1	0	0
ISM mfg.: Prices index	1	1	0	0
Building permits	1	0	1	0
Capacity utilization	1	0	1	0
PCE less food and energy: Chain price index	1	0	0	0
CPI-U: All items less food and energy	1	0	0	0
Inventories: Total business	1	0	1	0
Nonfarm business sector: Unit labor cost	1	0	0	1
JOLTS: Job openings: Total	1	0	0	1
Real personal consumption expenditures	1	0	1	0
PCE: Chain price index	1	0	0	0
ISM mfg: Employment index	1	1	0	0
Export Price Index	1	0	0	0
Manufacturers shipments: Durable Goods	1	0	1	0
Mfrs unfilled orders: All manufacturers industries	1	0	1	0
Manufacturers inventories: Durable goods	1	0	1	0
Real gross domestic income	1	0	1	0
Real disposable personal income	1	0	1	0
Exports: Goods and services	1	0	1	0
Imports: Goods and services	1	0	1	0

1 indicating that the variable in question belongs to the subgroup. Subgroups in abbreviation: G = Global, S = Soft, R = Real, L = Labor

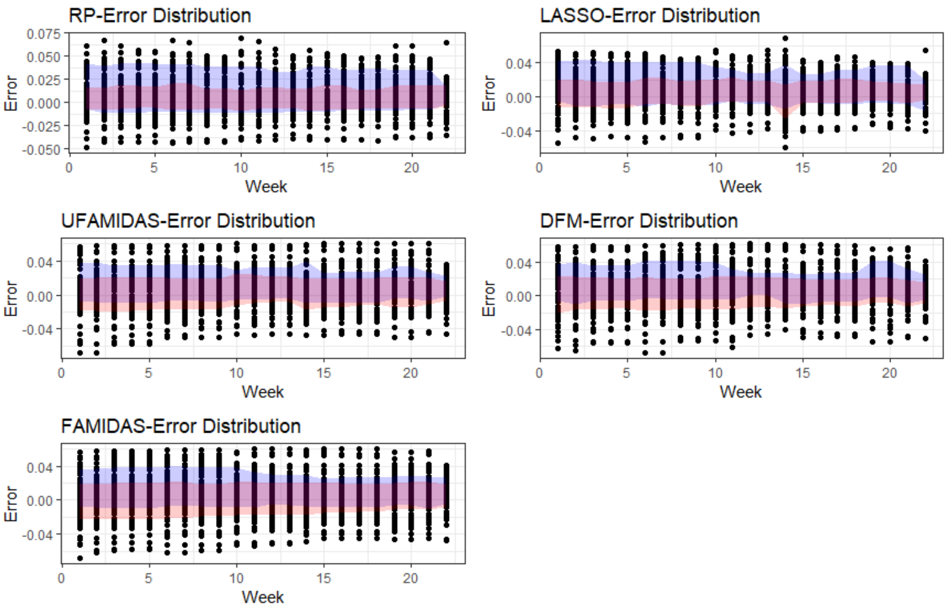

Figure 10: Error distributions over the period 2000Q1 - 2017Q4 (excluding 2008Q4 due to extreme errors in this quarter). The dots refer to the errors made in the respective week of the updating period in the quarters of the evaluation sample. The two colored 60% confidence bands correspond to two groups: the blue one indicates the errors made in first quarters, while the red one belongs to the other quarters.