Policy Research Brief No. 3

May 2021

EEU

Economic Evaluation Unit

Department of ECONOMICS
THE UNIVERSITY OF UTAH

Nowcasting Regional GDP in Utah Using Dynamic Factor Models

Matthew Gordon and Ivan Mendieta-Muñoz

Key findings

- Dynamic factor models can be used to obtain nowcasts for Utah's GDP using either expectation-maximization or two-stage principal components methods, thus providing a real-time read on the heartbeat of Utah's Economy

- Nowcasting Utah's GDP should be carried out using the two-stage principal components method. The models constructed using this method show moderate to large improvements in forecasting accuracy (11% to 28%) compared to other benchmark models, and can accurately track the peaks and troughs of Utah's GDP as more observations become available.

Introduction

Nowcasting refers to the prediction of real-time figures of the recent past, current time, or near future, that is, a forecast of the "now". Nowcasting is used primarily in two ways: (1) to perform real-time monitoring of economic indicators; and (2) to create estimates that fill the gap between the end of a time period and the release of data for that period. The relevance of nowcasting cannot be understated. Economic shocks such as the recent COVID-19 shutdown and the subsequent recession can occur rapidly, generating significant and deleterious impacts on the economy. Nowcasting allows us to track the effects of these rapid economic shocks in real-time, thus providing real-time information to policymakers and economists without needing to wait for the release of official data figures.

Dynamic factor models (DFMs) represent one of the most common econometric techniques to nowcast macroeconomic variables. In brief, a large number of economic variables are collected and the unobserved dynamic factors that drive these variables are estimated in a group. By combining these estimated factors together with old economic data and the most recently released data, it is possible to nowcast economic variables. Various institutions use DFMs to forecast the quarterly national GDP in real-time: the New York Federal Reserve Branch releases a weekly report known as the "Nowcasting Report" (see here); while the Atlanta Federal Reserve Branch releases a variant version of the factor model with their "GDPNow" program (see here)[1].

Nevertheless, dynamic factor nowcasts for GDP at the state level are extremely rare, which is likely due to limited data availability and to the assumption that national GDP acts as a good proxy for state GDP. The latter assumption can be incorrect, as the recent

1 DFMs work best with data that is released asynchronously. For example, for quarterly data such as GDP, it is possible to nowcast economic activity using monthly and weekly released economic variables and to update the nowcast model as more data becomes available.

COVID-19 economic recession has shown. The second quarter of 2020, when the COVID-19 recession began, had an annual official GDP growth rate of -31.4% for the nation, which was only of a -22.4% for the state of Utah (see BEA, 2020). Hence, there was a 10-percentage point difference between the GDP growth rate in the US and that of Utah in 2020.Q2. Differing GDP growth rates for the national and state levels necessitate state-level nowcasting in order to best capture state-level growth rates.

This purpose of this brief is to show that dynamic factor nowcasting is both feasible and relatively accurate for the state of Utah. We use a mixed database of national and state economic indicators in order to estimate DFMs using both expectation-maximization and two-stage principal components methods[2]. The results show that models constructed using the two-stage principal components method present large improvements in forecasting accuracy compared to other benchmark models (11% to 28%)

Expectation-maximization method

DFMs can be constructed using the expectation-maximization (EM) method, as described in Banbura et al. (2011) and used in the New York Federal Reserve's "Nowcasting Report". This method allows for the construction of a series of blocks in which common variables are grouped in the estimation, thus reducing the overall noise of the data and generating more accurate estimates. In the construction of the model, information criteria from Bai and Ng (2002) and considerations of computational limitations can be used to determine the model specification.

We estimated five four-factor models via the EM method[3]. The first and second models use the Block 0 structure and estimate national and Utah GDP, respectively, using a Vector Autoregression (VAR) process of order 2, VAR(2) process. The third, fourth, and fifth models use the Block 1, 2, and 3 structures, respectively, to estimate Utah GDP using a single-factor VAR(1) process[4]. Out-of-sample one-step quarterly nowcasts were performed on four different time periods and, to further replicate the conditions of real-world applications, an expanding time window in which out-of-sample nowcasts incorporate all available information for a given estimation date was employed. The first and second time periods were for nowcasts that occurred at the beginning of the last month of an estimated quarter or at the first day after an estimated quarter, respectively, for 2016.Q1-2020.Q3. The third and fourth time periods were for nowcasts that occurred at the beginning of the last month of an estimated quarter for 2013.Q1-2017.Q4 and 2010.Q1-2020.Q3, respectively.

The accuracy of each nowcast was calculated using the root mean square error (RMSE). A Theil's U statistic was calculated to show the accuracy of each respective model benchmarked to that of an ARIMA(2,0,0) model[5]. The Theil's U statistics obtained from the out-of-sample nowcasts is shown in Table 1; whereas Table 2 shows the calculated percentage improvement of each model compared to the baseline ARIMA.

Table 1: Theil's U of dynamic factor models relative to benchmark ARIMA (2,0,0) model

Model Type	Forecast Dates			
	2016:Q1-2020:Q3 - Last Month	2016:Q1-2020:Q3 - Quarter End	2013:Q1-2017:Q4	2010:Q1-2020:Q3
National EM	0.959	0.924	0.876	0.944
National 2S-PC	0.916	0.781	0.838	0.900
Utah EM Block 0	1.086	0.986	1.173	1.123
Utah EM Block 1	0.986	0.949	0.949	0.998
Utah EM Block 2	0.921	0.922	0.997	0.986
Utah EM Block 3	1.023	0.972	0.798	0.999
Utah 2S-PC Regional/National	0.890	0.719	1.040	1.035
Utah 2S-PC Regional Only	0.961	0.909	0.910	1.073

2 Appendix A presents a detailed description of the data used in this brief.

3 Details about the block structure employed are presented in Table B.1 in Appendix B; while Table B.2 presents the specific block organization for the estimated models

4 With respect to the first and second models, the information criteria suggest a VAR(3) process; however, we used a VAR(2) process instead because of computational limitations derived from the former estimation. Regarding the third, fourth and fifth models, a VAR(1) single-factor specification was used due to computational limitations associated with the estimation of complex block structures with multiple factors.

5 A Theil's U greater than 1 represents that the model is less accurate than the benchmark ARIMA by a percent of Theil's-U minus 1. A Theil's U less than 1 represents that the model is more accurate than the benchmark ARIMA by a percentage of 1 minus Theil's-U.

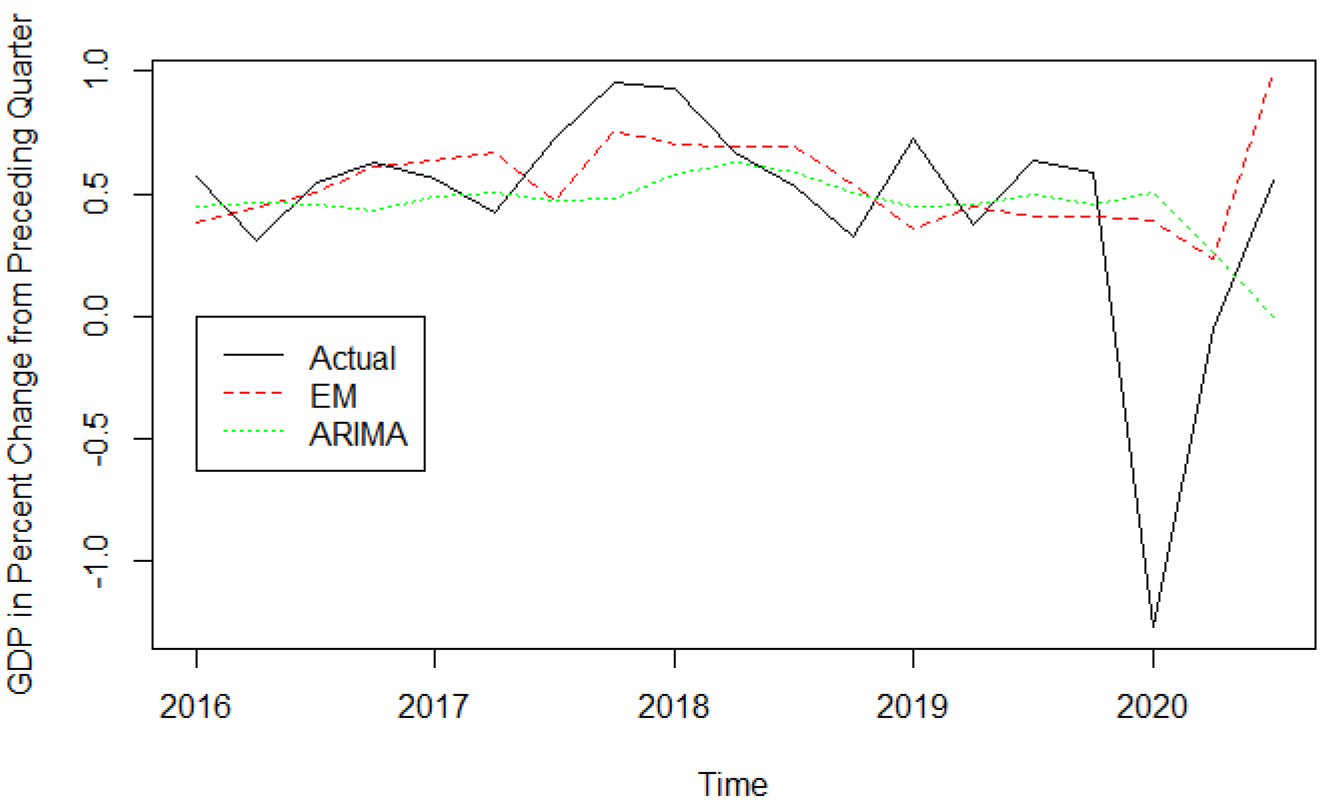
Table 2: Theil's U of dynamic factor models relative to benchmark ARIMA (2,0,0) model

Model Type	Forecast Dates			
	2016:Q1-2020:Q3 - Last Month	2016:Q1-2020:Q3 - Quarter End	2013:Q1-2017:Q4	2010:Q1-2020:Q3
National EM	4.1%	7.6%	12.4%	5.6%
National 2S-PC	8.4%	21.9%	16.2%	10.0%
Utah EM Block 0	-8.6%	1.4%	-17.3%	-12.3%
Utah EM Block 1	1.4%	5.1%	5.1%	0.2%
Utah EM Block 2	7.9%	7.8%	0.3%	1.4%
Utah EM Block 3	-2.3%	2.8%	20.2%	0.1%
Utah 2S-PC Regional/National	11.0%	28.1%	-4.0%	-3.5%
Utah 2S-PC Regional Only	3.9%	9.1%	9.0%	-7.3%

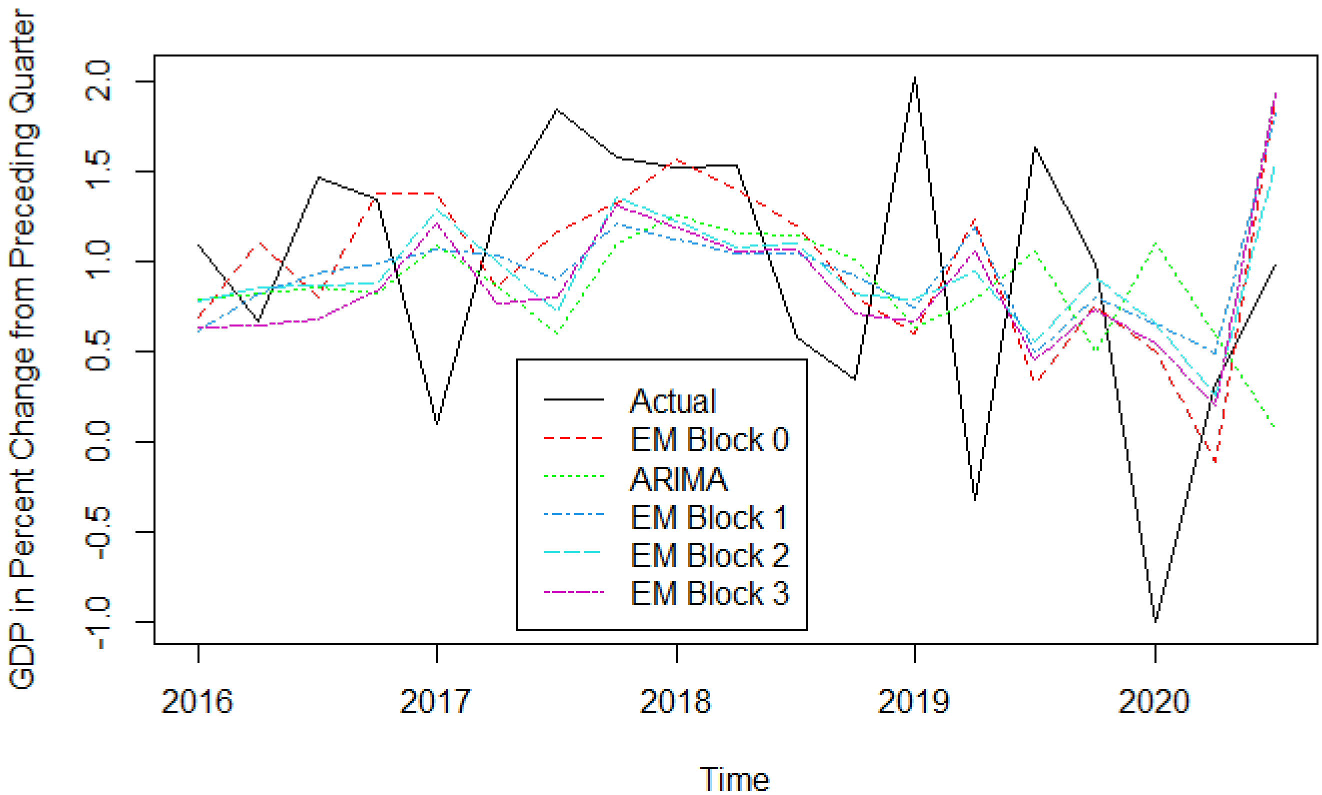
It appears that the national estimates using the EM model show moderate improvements in nowcasting accuracy compared to the baseline ARIMA model. For Utah estimates, the second EM model, which uses the Block 0 structure, shows worse or only slightly better results than the ARIMA model. The third, fourth, and fifth models generally show small to moderate improvements in accuracy over the ARIMA model, with the Utah EM model using Block 2 showing the best improvements by approximately 8% for the most recent periods.

Graphs 1 and 2 below visualize the out-of-sample nowcasting results for the period 2016.Q1-2020.Q3-Quarter End.

Graph 1: National nowcasts at end of quarter obtained from the expectation-maximization method (EM), 2016.Q1-2020.Q3



Graph 2: Utah nowcasts at end of quarter obtained from the expectation-maximization method (EM), 2016.Q1-2020.Q3



Although it is possible to use the EM method to produce nowcasts of GDP for the state of Utah, these models present only small to moderate improvements over ARIMA models. Nevertheless, with better data, more computational power, and changes to the specification of the models, the EM method may be used as a new tool for policymakers and economists to generate real-time information about Utah's economy.

Two-stage principal components method

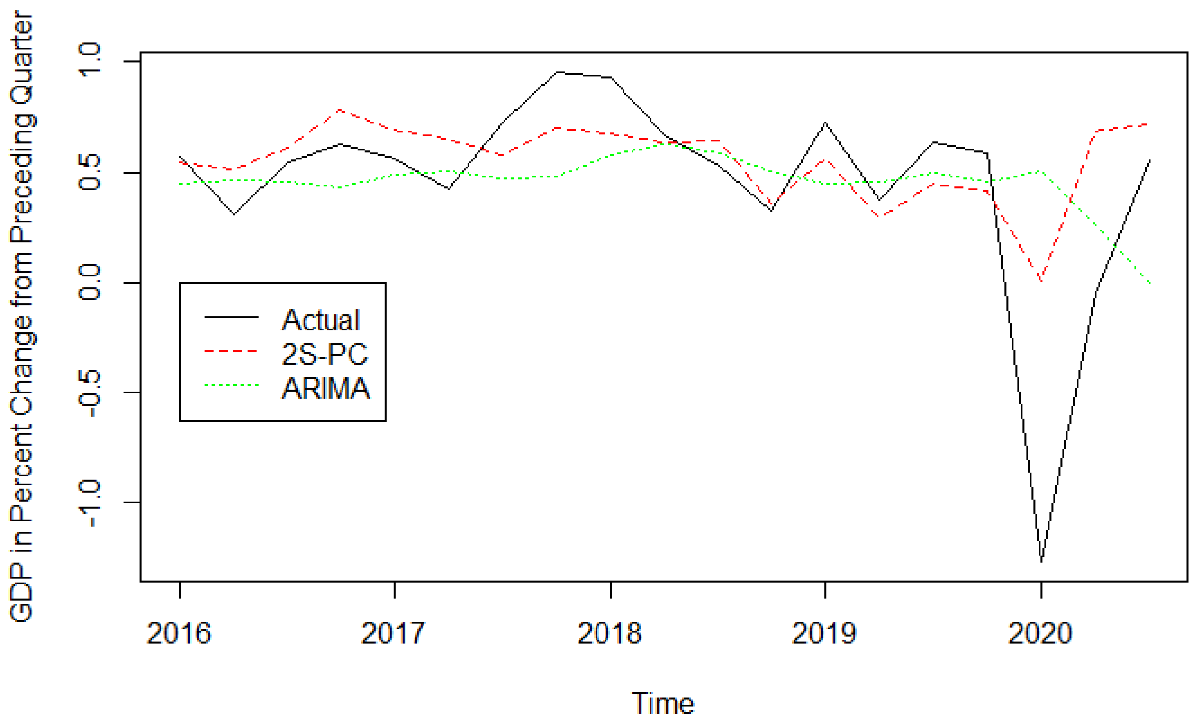
A second method in constructing DFMs is the two-stage principal components (2S-PC) method, as described in Giannone et al. (2008). This method has the advantage of being less computationally intensive than the EM method, so that there is no need to consider computation limitations in the estimation of the models. The 2S-PC method, however, does not allow for the organization of the time series data into blocks. Information criteria tests following Bai and Ng (2002) can be used to determine the number of factors, while information criteria following Bai and Ng (2007) can be used to determine the number of shocks.

Information criteria tests suggest a four-factor, four-shock, VAR(3) process for the DFMs estimated via the 2S-PC method. Three models using this specification were estimated. The first one estimated national GDP, the one second estimated Utah GDP using both national and Utah data, and the third one estimated Utah GDP using only data for Utah. Out-of-sample one-step quarterly nowcasts were performed on the same time periods used in the EM estimation. The time required to complete these out-of-sample nowcasts was around 1/30th that of the time required for the EM method.

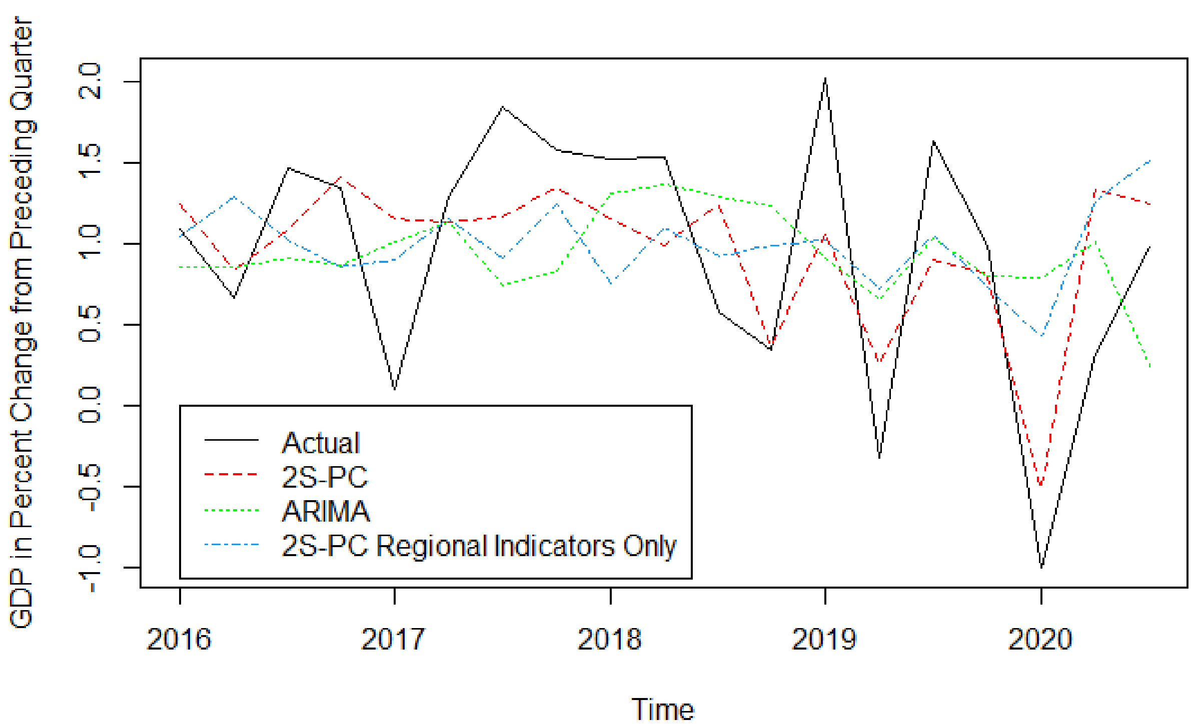
Tables 1 and 2 present the accuracy of these 2S-PC nowcasts in terms of the Theil's U statistic and the percentage improvement compared to the benchmark ARIMA(2,0,0) model. Overall, all three models suggest moderate to large improvements over the ARIMA model, although the Utah-level models seem to struggle more with nowcasts of earlier periods. This can be because Utah-level data is sparse and early time periods do not provide enough observations to accurately fit the models. However, Utah-level nowcasts for the most recent time periods show that the 2S-PC method outperforms both ARIMA and EM models by a moderate to large degree and a small to a moderate degree, respectively, when both national and regional data is included.

Graphs 3 and 4 below plot the out-of-sample nowcasting results for the period 2016.Q1-2020.Q3-Quarter End.

Graph 3: National nowcasts at end of quarter obtained from the two-stage principal component method (2S-PC), 2016.Q1-2020.Q3



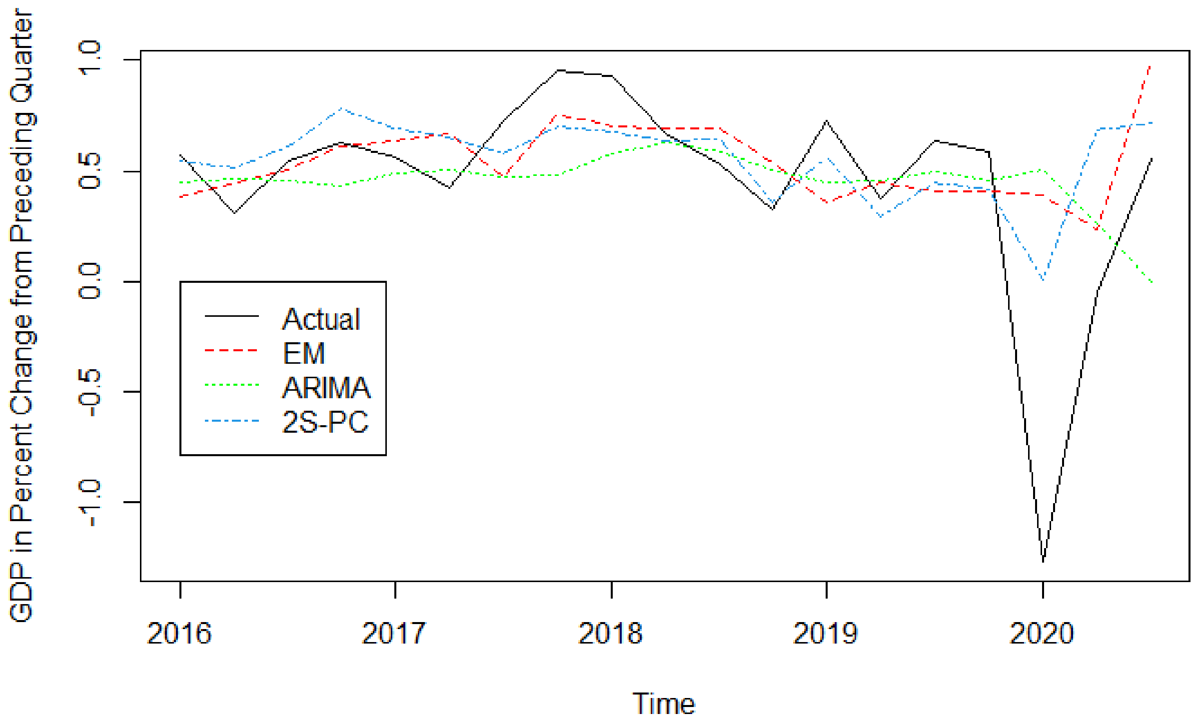
Graph 4: Utah nowcasts at end of quarter obtained from the two-stage principal component method (2S-PC), 2016.Q1-2020.Q3



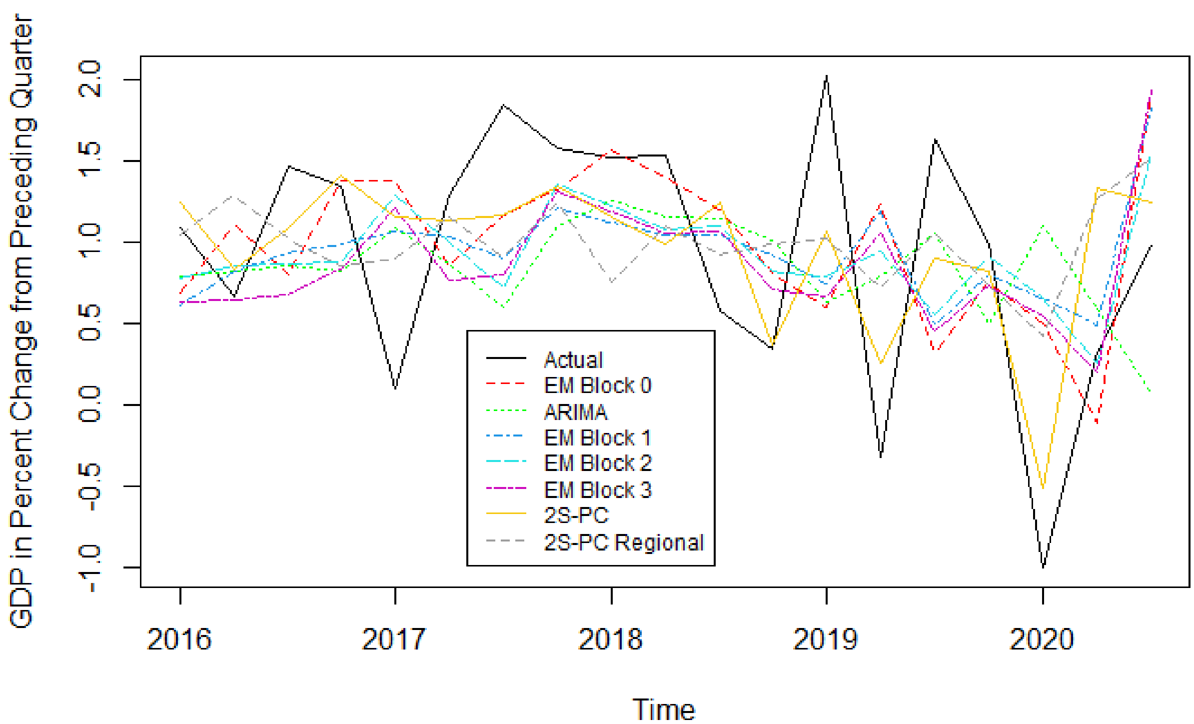
Note that the nowcasts for Utah's GDP generated using the 2S-PC method, including both national and regional data series, seem to more closely track the peaks and troughs of Utah's GDP for more recent quarters. Hence, relatively more accurate nowcasts of GDP for the state of Utah using DFMs can be estimated via the 2S-PC method.

Finally, summaries of all the out-of-sample nowcasting results obtained from the ARIMA, EM, and 2S-PC models for the period 2016.Q1-2020.Q3-Quarter End are presented in Graphs 5 and 6 below.

Graph 5: All national nowcasts at end of quarter, 2016.Q1-2020.Q3



Graph 6: All Utah nowcasts at end of quarter, 2016.Q1-2020.Q3



Conclusion

This brief uses dynamic factor models in order to nowcast Utah's GDP, showing that it possible to use both the expectation-maximization and two-stage principal components estimation methods to get a pulse on the heartbeat of Utah's economy. Dynamic factor models show improvements over other standard forecasting tools, such as ARIMA models. However, the models constructed using the two-stage principal component method considering a mixed database of both national and Utah-level data are the ones that provide the most accurate nowcasts of Utah's GDP and, therefore, should be preferred over both ARIMA models and dynamic factor models estimated via the expectation-maximization method. Furthermore, it appears that, despite data limitations, as more time passes the two-stage principal component method becomes increasingly more accurate and can satisfactorily track the peaks and troughs observed in Utah's GDP.

It seems likely that, as more data becomes available, nowcasts obtained from dynamic factor models estimated via the two-stage principal component method will become increasingly more accurate. This is useful to obtain real-time estimates of Utah's GDP before official state-wide figures are available, so such estimates can be used by local economists and policymakers to design effective economic policies under uncertain, rapidly changing economic conditions. Dynamic factor models estimated via the two-stage principal component method represent a promising tool for real-time economic monitoring in the state of Utah.

EEU
Economic Evaluation Unit

Department of ECONOMICS
THE UNIVERSITY OF UTAH

Aknowledgements

This work was supported by funding from the Undergraduate Research Opportunities Program (UROP) at the University of Utah, awarded to Matthew Gordon. This brief uses the FRED® API but is not endorsed or certified by the Federal Reserve Bank of St. Louis. Please see Appendix A for citations of appropriate data series. This work uses the "nowcasting" package in R by de Valk et al. (2019).

Department of ECONOMICS THE UNIVERSITY OF UTAH

EEU Economic Evaluation Unit

Office of UNDERGRADUATE RESEARCH THE UNIVERSITY OF UTAH

References

Bai, J., and Ng, S. (2002). Determining the number of factors in approximate factor models. Econometrica, 70(1): 191-221.

Bai, J., and Ng, S. (2007). Determining the number of primitive shocks in factor models. Journal of Business and Economic Statistics, 25(1), 52-60.

Banbura, M., Giannone, D., and Reichlin, L. (2011). Nowcasting. In Clements, M. and Hendry, D. (Eds.) The Oxford Handbook on Economic Forecasting. New York City: Oxford University Press, pp. 193-224.

Bureau of Economic Analysis (BEA). (2020). Gross Domestic Product by State, 2nd Quarter 2020. 2 Oct. 2020. Available at: <www.bea.gov/news/2020/gross-domestic-product-state-2nd-quarter-2020> (accessed 4/30/2021).

De Valk, S., de Mattos, D., and Ferreira, P. (2019). Nowcasting: An R package for predicting economic variables using dynamic factor models. The R Journal, 11(1): 1-15.

Federal Reserve Bank of New York. Nowcasting Report. Available at: <https://www.newyorkfed.org/research/policy/nowcast.html> (accessed 4/30/2021).

Federal Reserve Bank of Atlanta. GDPNow. Available at: <https://www.atlantafed.org/cqer/research/gdpnow> (accessed 4/30/2021).

Giannone, D., Reichlin, L., and Small, D. (2008). Nowcasting: The real-time informational content of macroeconomic data. Journal of Monetary Economics, 55(4): 665-676.

Appendix A. Data

Data for this brief was obtained from the Federal Reserve Bank of St. Louis via the FRED API. Data series for the national level were chosen following Giannone et al. (2008), the NYFED in their “Nowcasting Report”, and identifying data series likely to be related to GPD. Utah level data series were collected by selecting the analogous versions of the national data series, when available, and by selecting data series likely related to Utah GDP. Data availability for Utah GDP was limited to 2005.Q1, so all data was collected starting from this period until 2020.Q3. All data were transformed into stationary series and seasonally adjusted using the X11 algorithm used by the Census Bureau. Table A.1 shows the chosen data series show by their respective FRED ID name, the frequency of each series, and the transformed units that made the data stationary. Citations of non-public data series are at the end of this Appendix.

Table A.1: Data series for nowcasting models

FRED ID	Frequency	Transformation
GDPC1	Quarterly	Quarterly Rate of Change
PAYEMS	Monthly	Monthly Difference
UNRATE	Monthly	Monthly Difference
NPPTTL	Monthly	Monthly Difference
ICSA	Monthly	Monthly Rate of Change
CIVPART	Monthly	Monthly Difference
AWHAETP	Monthly	Monthly Rate of Change
AWHNONAG	Monthly	Monthly Rate of Change
DGORDER	Monthly	Monthly Rate of Change
AMNMNO	Monthly	Monthly Rate of Change
AMTMNO	Monthly	Monthly Rate of Change
ANDENO	Monthly	Monthly Rate of Change
PPIFIS	Monthly	Monthly Rate of Change
WPSFD4131	Monthly	Monthly Rate of Change
WPSFD49207	Monthly	Monthly Rate of Change
PCESC96	Monthly	Monthly Rate of Change
PCEDGC96	Monthly	Monthly Rate of Change
PCEC96	Monthly	Monthly Rate of Change
DPCCRAM1M225NBEA	Monthly	Monthly Difference
TCU	Monthly	Monthly Difference
IPFINAL	Monthly	Monthly Rate of Change
INDPRO	Monthly	Monthly Rate of Change
CAPUTLG3311A2S	Monthly	Monthly Rate of Change
MCUMFN	Monthly	Monthly Rate of Change
IPUTIL	Monthly	Monthly Rate of Change
IPG211111CS	Monthly	Monthly Rate of Change
CPIAUCSL	Monthly	Monthly Difference
RSAFS	Monthly	Monthly Rate of Change
HSN1F	Monthly	Monthly Rate of Change
HOUST	Monthly	Monthly Rate of Change
GACDISA066MSFRBNY	Monthly	Levels
I42IMSM144SCEN	Monthly	Monthly Rate of Change
TTLCONS	Monthly	Monthly Rate of Change
GACDFSA066MSFRBPHI	Monthly	Levels
PERMIT	Monthly	Monthly Difference
PCEPILFE	Monthly	Monthly Difference
CPILFESL	Monthly	Monthly Difference
BUSINV	Monthly	Monthly Rate of Change
ULCNFB	Quarterly	Quarterly Rate of Change
JTSJOL	Monthly	Monthly Difference

Table A.1: Data series for nowcasting models (continued from previous page)

FRED ID	Frequency	Transformation
PCEPI	Monthly	Monthly Difference
AMDMVS	Monthly	Monthly Rate of Change
AMTMUO	Monthly	Monthly Rate of Change
AMDMTI	Monthly	Monthly Rate of Change
A261RX1Q020SBEA	Quarterly	Quarterly Rate of Change
DSPIC96	Monthly	Monthly Rate of Change
BOPTEXP	Monthly	Monthly Rate of Change
BOPTIMP	Monthly	Monthly Rate of Change
DGS2	Monthly	Monthly Difference
DGS5	Monthly	Monthly Difference
M1	Monthly	Monthly Rate of Change
M2	Monthly	Monthly Rate of Change
IPMAN	Monthly	Monthly Rate of Change
PSAVERT	Monthly	Monthly Difference
CCSA	Monthly	Monthly Rate of Change
TSIFRGHTC	Monthly	Levels
IPCONGD	Monthly	Monthly Rate of Change
IPBUSEQ	Monthly	Monthly Rate of Change
IPMAT	Monthly	Monthly Rate of Change
CES0500000003	Monthly	Monthly Rate of Change
MZM	Monthly	Monthly Rate of Change
WIMFSL	Monthly	Monthly Difference
W055RC1	Monthly	Monthly Rate of Change
FRBKCLMCILA	Monthly	Monthly Difference
FRBKCLMCIM	Monthly	Levels
NEIPTERM156SFRBRIC	Monthly	Monthly Difference
COMPOUT	Monthly	Monthly Rate of Change
NFINCP	Monthly	Monthly Rate of Change
UTRQGSP	Quarterly	Quarterly Rate of Change
UTUR	Monthly	Monthly Difference
UTLF	Monthly	Monthly Rate of Change
SMU49000000500000003SA	Monthly	Monthly Rate of Change
SMU49000000500000002SA	Monthly	Monthly Difference
LBSSA49	Monthly	Monthly Difference
UTNA	Monthly	Monthly Difference
UTBPPRIVSA	Monthly	Monthly Rate of Change
UTOTOT	Quarterly	Quarterly Rate of Change
UTWTOT	Quarterly	Quarterly Rate of Change
HBUSAPPWNSAUT	Monthly	Monthly Difference
BUSAPPWNSAUT	Monthly	Monthly Difference
UTSLIND	Monthly	Monthly Difference

Table A.1: Data series for nowcasting models (continued from previous page)

FRED ID	Frequency	Transformation
UTPHCI	Monthly	Monthly Difference
PCUOMFGOMFG	Monthly	Monthly Rate of Change
IR	Monthly	Monthly Difference
IQ	Monthly	Monthly Rate of Change
FEDFUNDS	Monthly	Monthly Difference
TB3MS	Monthly	Monthly Difference
TB6MS	Monthly	Monthly Difference
DGS1	Monthly	Monthly Difference
DGS3	Monthly	Monthly Difference
DGS7	Monthly	Monthly Difference
DGS10	Monthly	Monthly Difference
BUSLOANSNSA	Monthly	Monthly Rate of Change
CURRCIR	Monthly	Monthly Rate of Change
DEXUSEU	Monthly	Monthly Rate of Change
EXJPUS	Monthly	Monthly Rate of Change
EXUSUK	Monthly	Monthly Rate of Change
TLAACBM027NBOG	Monthly	Monthly Rate of Change
TOTALNSA	Monthly	Monthly Difference
TWEXBGSMTH	Monthly	Monthly Difference
BOGMBASE	Monthly	Monthly Rate of Change
NASDAQCOM	Monthly	Monthly Rate of Change
USEPUINDXM	Monthly	Monthly Difference
MTSDS133FMS	Monthly	Monthly Rate of Change
KCFSI	Monthly	Levels
NFCIRISK	Monthly	Monthly Difference
NFCILEVERAGE	Monthly	Monthly Difference
NFCI	Monthly	Monthly Difference
CFNAI	Monthly	Monthly Difference
STLFSI2	Monthly	Monthly Difference
DCPF1M	Monthly	Monthly Difference
UTICLAIMS	Monthly	Monthly Rate of Change
UTCCLAIMS	Monthly	Monthly Rate of Change
BRUT49M647NCEN	Monthly	Monthly Rate of Change
LAUST490000000000004	Monthly	Monthly Difference
IMPTOTUT	Monthly	Monthly Rate of Change
EXPTOTUT	Monthly	Monthly Rate of Change
UTINSUREDUR	Monthly	Levels
RTWVDUT684NMFRBDAL	Monthly	Monthly Rate of Change
CBUSAPPWNSAUT	Monthly	Monthly Difference
WBUSAPPWNSAUT	Monthly	Monthly Difference

Citations of non-public data series

Automatic Data Processing, Inc., Total Nonfarm Private Payroll Employment [NPPTTL], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/NPPTTL, April 25, 2021.

Federal Reserve Bank of New York, Current General Business Conditions; Diffusion Index for New York [GACDISA066MSFRBNY], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/GACDISA066MSFRBNY, April 24, 2021.

Federal Reserve Bank of Philadelphia, Current General Activity; Diffusion Index for Federal Reserve District 3: Philadelphia [GACDFSA066MSFRBPHI], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/GACDFSA066MSFRBPHI, April 25, 2021.

NASDAQ OMX Group, NASDAQ Composite Index [NASDAQCOM], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/NASDAQCOM, April 24, 2021.

Federal Reserve Bank of Kansas City, Kansas City Financial Stress Index [KCFSI], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/KCFSI, April 25, 2021.

Federal Reserve Bank of Kansas City, KC Fed Labor Market Conditions Index, Level of Activity Indicator [FRBKCLMCILA], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/FRBKCLMCILA, April 25, 2021.

Federal Reserve Bank of Kansas City, KC Fed Labor Market Conditions Index, Momentum Indicator [FRBKCLMCIM], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/FRBKCLMCIM, April 24, 2021.

Federal Reserve Bank of Chicago, Chicago Fed National Financial Conditions Risk Subindex [NFCIRISK], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/NFCIRISK, April 25, 2021.

Federal Reserve Bank of Chicago, Chicago Fed National Financial Conditions Leverage Subindex [NFCILEVERAGE], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/NFCILEVERAGE, April 24, 2021.

Federal Reserve Bank of Chicago, Chicago Fed National Financial Conditions Index [NFCI], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/NFCI, April 25, 2021.

Federal Reserve Bank of Chicago, Chicago Fed National Activity Index [CFNAI], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/CFNAI, April 25, 2021.

Federal Reserve Bank of St. Louis, St. Louis Fed Financial Stress Index [STLFSI2], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/STLFSI2, April 25, 2021.

Federal Reserve Bank of Richmond, Hornstein-Kudlyak-Lange Non-Employment Index including People Working Part-Time for Economic Reasons [NEIPTERM156SFRBRIC], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/NEIPTERM156SFRBRIC, April 24, 2021.

Federal Reserve Bank of Dallas, Real Trade-Weighted Value of the dollar for Utah [RTWVDUT684NMFRBDAL], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/RTWVDUT684NMFRBDAL, April 25, 2021.

Federal Reserve Bank of Philadelphia, Leading Index for Utah [UTSLIND], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/UTSLIND, April 25, 2021.

Federal Reserve Bank of Philadelphia, Coincident Economic Activity Index for Utah [UTPHCI], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/UTPHCI, April 25, 2021.

Appendix B. Dynamic factor models estimated via the expectations-maximization method

Table B.1: Block structure of the expectations-maximization dynamic factor models

FRED ID	Global	National	Regional	National Real	National Labor	Financial	Regional Real	Regional Labor
GDPC1	1	1	0	1	0	0	0	0
PAYEMS	1	1	0	0	1	0	0	0
UNRATE	1	1	0	0	1	0	0	0
NPPTTL	1	1	0	0	1	0	0	0
ICSA	1	1	0	0	1	0	0	0
CIVPART	1	1	0	0	1	0	0	0
AWHAETP	1	1	0	0	1	0	0	0
AWHNONAG	1	1	0	0	1	0	0	0
DGORDER	1	1	0	1	0	0	0	0
AMNMNO	1	1	0	1	0	0	0	0
AMTMNO	1	1	0	1	0	0	0	0
ANDENO	1	1	0	1	0	0	0	0
PPIFIS	1	1	0	0	0	0	0	0
WPSFD4131	1	1	0	0	0	0	0	0
WPSFD49207	1	1	0	0	0	0	0	0
PCESC96	1	1	0	1	0	0	0	0
PCEDGC96	1	1	0	1	0	0	0	0
PCEC96	1	1	0	1	0	0	0	0
DPCCRAM1M225NBEA	1	1	0	1	0	0	0	0
TCU	1	1	0	1	0	0	0	0
IPFINAL	1	1	0	1	0	0	0	0
INDPRO	1	1	0	1	0	0	0	0
CAPUTLG3311A2S	1	1	0	1	0	0	0	0
MCUMFN	1	1	0	1	0	0	0	0
IPUTIL	1	1	0	1	0	0	0	0
IPG211111CS	1	1	0	1	0	0	0	0
CPIAUCSL	1	1	0	0	0	0	0	0

Table B.1: Block structure of the expectations-maximization dynamic factor models (continued from previous page)

FRED ID	Global	National	Regional	National Real	National Labor	Financial	Regional Real	Regional Labor
RSAFS	1	1	0	1	0	0	0	0
HSN1F	1	1	0	1	0	0	0	0
HOUST	1	1	0	1	0	0	0	0
GACDISA066MSFRBNY	1	1	0	0	0	0	0	0
I42IMSM144SCEN	1	1	0	1	0	0	0	0
TTLCONS	1	1	0	1	0	0	0	0
GACDFSA066MSFRBPHI	1	1	0	0	0	0	0	0
PERMIT	1	1	0	1	0	0	0	0
PCEPILFE	1	1	0	0	0	0	0	0
CPILFESL	1	1	0	0	0	0	0	0
BUSINV	1	1	0	1	0	0	0	0
ULCNFB	1	1	0	0	1	0	0	0
JTSJOL	1	1	0	0	1	0	0	0
PCEPI	1	1	0	0	0	0	0	0
AMDMVS	1	1	0	1	0	0	0	0
AMTMUO	1	1	0	1	0	0	0	0
AMDMTI	1	1	0	1	0	0	0	0
A261RX1Q020SBEA	1	1	0	1	0	0	0	0
DSPIC96	1	1	0	1	0	0	0	0
BOPTEXP	1	1	0	1	0	0	0	0
BOPTIMP	1	1	0	1	0	0	0	0
DGS2	1	1	0	0	0	1	0	0
DGS5	1	1	0	0	0	1	0	0
M1	1	1	0	0	0	1	0	0
M2	1	1	0	0	0	1	0	0
IPMAN	1	1	0	1	0	0	0	0
PSAVERT	1	1	0	1	0	0	0	0
CCSA	1	1	0	0	1	0	0	0
TSIFRGHTC	1	1	0	1	0	0	0	0

Table B.1: Block structure of the expectations-maximization dynamic factor models (continued from previous page)

FRED ID	Global	National	Regional	National Real	National Labor	Financial	Regional Real	Regional Labor
IPCONGD	1	1	0	1	0	0	0	0
IPBUSEQ	1	1	0	1	0	0	0	0
IPMAT	1	1	0	1	0	0	0	0
CES0500000003	1	1	0	0	1	0	0	0
MZM	1	1	0	0	0	1	0	0
WIMFSL	1	1	0	0	0	1	0	0
W055RC1	1	1	0	1	0	0	0	0
FRBKCLMCILA	1	1	0	0	1	0	0	0
FRBKCLMCIM	1	1	0	0	1	0	0	0
NEIPTERM156SFRBRIC	1	1	0	0	1	0	0	0
COMPOUT	1	1	0	0	0	1	0	0
NFINCP	1	1	0	0	0	1	0	0
UTRQGSP	1	0	1	0	0	0	1	0
UTUR	1	0	1	0	0	0	0	1
UTLF	1	0	1	0	0	0	0	1
SMU49000000500000003SA	1	0	1	0	0	0	0	1
SMU49000000500000002SA	1	0	1	0	0	0	0	1
LBSSA49	1	0	1	0	0	0	0	1
UTNA	1	0	1	0	0	0	0	1
UTBPPRIVSA	1	0	1	0	0	0	1	0
UTOTOT	1	0	1	0	0	0	1	0
UTWTOT	1	0	1	0	0	0	1	0
HBUSAPPWNSAUT	1	0	1	0	0	0	1	0
BUSAPPWNSAUT	1	0	1	0	0	0	1	0
UTSLIND	1	0	1	0	0	0	1	0
UTPHCI	1	0	1	0	0	0	0	1
PCUOMFGOMFG	1	1	0	1	0	0	0	0
IR	1	1	0	0	0	0	0	0
IQ	1	1	0	0	0	0	0	0

Table B.1: Block structure of the expectations-maximization dynamic factor models (continued from previous page)

FRED ID	Global	National	Regional	National Real	National Labor	Financial	Regional Real	Regional Labor
FEDFUNDS	1	1	0	0	0	1	0	0
TB3MS	1	1	0	0	0	1	0	0
TB6MS	1	1	0	0	0	1	0	0
DGS1	1	1	0	0	0	1	0	0
DGS3	1	1	0	0	0	1	0	0
DGS7	1	1	0	0	0	1	0	0
DGS10	1	1	0	0	0	1	0	0
BUSLOANSNSA	1	1	0	0	0	1	0	0
CURRCIR	1	1	0	0	0	1	0	0
DEXUSEU	1	1	0	0	0	1	0	0
EXJPUS	1	1	0	0	0	1	0	0
EXUSUK	1	1	0	0	0	1	0	0
TLAACBM027NBOG	1	1	0	0	0	1	0	0
TOTALNSA	1	1	0	1	0	0	0	0
TWEXBGSMTH	1	1	0	0	0	1	0	0
BOGMBASE	1	1	0	0	0	1	0	0
NASDAQCOM	1	1	0	0	0	1	0	0
USEPUINDXM	1	1	0	0	0	0	0	0
MTSDS133FMS	1	1	0	1	0	0	0	0
KCFSI	1	1	0	0	0	1	0	0
NFCIRISK	1	1	0	0	0	1	0	0
NFCILEVERAGE	1	1	0	0	0	1	0	0
NFCI	1	1	0	0	0	1	0	0
CFNAI	1	1	0	1	0	0	0	0
STLFSI2	1	1	0	0	0	1	0	0
DCPF1M	1	1	0	0	0	1	0	0
UTICLAIMS	1	0	1	0	0	0	0	1
UTCCLAIMS	1	0	1	0	0	0	0	1
BRUT49M647NCEN	1	0	1	0	0	0	1	0

Table B.1: Block structure of the expectations-maximization dynamic factor models (continued from previous page)

FRED ID	Global	National	Regional	National Real	National Labor	Financial	Regional Real	Regional Labor
LAUST490000000000004	1	0	1	0	0	0	0	1
IMPTOTUT	1	0	1	0	0	0	1	0
EXPTOTUT	1	0	1	0	0	0	1	0
UTINSUREDUR	1	0	1	0	0	0	0	1
RTWVDUT684NMFRBDAL	1	0	1	0	0	0	1	0
CBUSAPPWNSAUT	1	0	1	0	0	0	1	0
WBUSAPPWNSAUT	1	0	1	0	0	0	1	0

Table B.2: Block organization of specific expectations-maximization dynamic factor models

	EM Model Name			
Block	Block 0	Block 1	Block 2	Block 3
Global	1	1	1	1
National	0	1	1	0
Regional	0	1	1	0
National Real	0	0	1	1
National Labor	0	0	1	1
Financial	0	0	1	1
Regional Real	0	0	1	1
Regional Labor	0	0	1	1