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Craig S. Hakkio and Jun Nie

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Federal Reserve Bank of Kansas City

Forecasting Foreign Economic Growth Using Cross-Country Data

Craig S. Hakkio and Jun Nie[1]

Abstract

We construct a monthly measure of foreign economic growth based on a wide range of cross-country indicators. Unlike GDP data which is normally released with a delay of 1-2 quarters in most countries, our monthly measure incorporates monthly information up to the current month. As new information arrives, this measure of foreign growth can be updated as frequently as daily. This monthly measure of foreign growth not only helps gauge the economic conditions in other countries, but also provides a timely measure of foreign demand to help forecast U.S. export growth.

1. Introduction

GDP growth is the commonly used measure of economic growth in a country. However, in most countries, GDP data is released with significant delay, usually 1-2 quarters. This makes any analysis requiring a timely measure of economic growth very difficult. For example, forecasting export growth is often done by using GDP to approximate foreign demand, but the large delay of GDP data presents challenges for generating accurate export growth forecasts.

The goal in this paper is to construct a more timely measure of foreign growth based on cross-country monthly data. Since data in different countries are released on different schedules,

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[1] Craig S. Hakkio is a former senior vice president and special advisor and Jun Nie is a senior economist at the Federal Reserve Bank of Kansas City. The views expressed in this paper only represent those from the authors and do not represent the views from the Federal Reserve Bank of Kansas City or the Federal Reserve System.

in practice, our measure can incorporate all information up to the current month and can be updated as frequently as daily. This feature makes our measure more timely than GDP data in measuring foreign demand and forecasting exports. In addition, to better explain the forecast, we group data into several categories and construct a similar analysis on each group. In this way, we can study how changes in each group of data contribute to changes in our foreign growth forecast. This is particularly useful if forecasters are interested in the evolution of the forecast over time, which is usually the case for many researchers and policy-makers in central banks.

This paper is related to Nie and Oksol (2018) which uses a nighttime light index constructed from satellite images to measure economic conditions on the earth. The basic idea is that more nighttime lights usually indicate more economic activities in a given region. They showed that a nighttime light index can be used to more precisely forecast export growth than GDP data. They pointed out the main value of satellite data is its timeliness due to recent technological improvement—monthly satellite data became available in 2012 and daily data became available in 2017. As they also pointed out, traditional data such as GDP data still does a better job than satellite data in forecasting exports when both are available at the same frequency. So, rather than relying on unconventional data, this paper focuses on traditional data but tries to use monthly data from a large set of countries to construct a timely measure of foreign growth.

Our paper is also related to Nie and Taylor (2013) which show U.S. export growth has different elasticities with economic growth in different regions. In their analysis they use GDP as a measure of foreign demand and show changes in European growth matter most for U.S. export growth. Similarly, our analysis can also be applied to different groups of countries. For example, we use monthly data to construct growth for advanced economies, emerging economies, and key

U.S. trade partners. In this way, we can better study how growth in each region/country influences U.S. export growth.

As our main method is based on the principle component estimator of factors, our paper is related to a large literature on using factor models to conduct forecasting such as Stock and Watson (2002). Our main contribution in this paper is to focus on aggregate GDP growth in the world (excluding the U.S.) while many other studies focus on a particular country or region.

The rest of the paper is organized as follows. Section 2 describes the methodology. Section 3 describes the data. Section 4 reports results. Section 5 concludes.

2. Methodology

Our approach is based on a factor model using cross-country data. Our forecast procedure consists of three steps. In the first step, we forecast missing values in our monthly data to make the data set balanced and as recent as possible. In the second step, we estimate several factor models for different group of countries and for different types of data. As we will show later, this will greatly help in understanding our forecasts and forecast revisions. In the third step, we estimate the relationship, at the quarterly frequency, between estimated factors and foreign GDP growth, and use this estimated relationship and the forecasted factors to form forecasts of quarterly foreign GDP growth.

Step 1. Forecasting Missing Values

Our data covers a large set of countries. One important feature of such cross-country data is that different types of data are released at different schedules across countries. For example, consumer confidence data for China is usually released with one month of delay, while Canadian industrial production data normally arrives with two months of delay. In addition, for the same type of data, such as PMI, they are released at the beginning of the month in Sweden, while they are released at the end of the month in Israel. To include as much recent data as possible, which is crucial for our forecast purpose, we need to forecast unavailable values to balance the data set. In particular, we estimate an AR (n) process to forecast the missing values in each data series where the number of lags, n, is optimally chosen for each series. As one example, Table 1 shows the differences in data availability as of July 5, 2018, when the factor model is estimated.

Step 2. Estimating Factors

We use the principle component analysis (PCA) to extract factors from the monthly cross-country data. The model is described as follows:

$$X_t = \Lambda F_t + e_t$$

where X_t is a high-dimension vector which contains selected monthly data. F_t is a low-dimension vector containing the factors that drive movements of data X_t. Λ is the factor loading which measures the influences of the factors on each data series.

The PCA analysis is applied to different groups of monthly data separately, such as different groups of countries (i.e., advanced and developing economies) and different types of data as defined in Table 2 (i.e., hard data, soft data, forecast data, and PMI data). The former helps capture the possible difference between advanced countries and developing countries. In studying export growth, capturing this heterogeneity is important as different regions matter differently for U.S. export growth (Nie and Taylor, 2013). In addition, the latter helps us to better understand the driving forces of the strength or weakness in foreign growth.

Step 3. Forecasting Foreign GDP Growth

The factors extracted from the PCA capture the common movements in a wide range of monthly indicators. In order to use these factors to provide forecasts of foreign GDP growth, we first use a VAR to forecast future values of the factors. We then estimate the relationships between the factors and foreign GDP growth.[2] As GDP data is quarterly, we first construct quarterly factors by taking the quarterly averages of the monthly factors. Then we estimate a VAR model which includes GDP growth and factors for both advanced countries and developing countries. This provides the historical relationship between GDP growth and our estimated factors. Finally, we use this estimated VAR model and the separately forecasted factors to forecast foreign GDP growth. Notice in this final step we do not use the VAR model to jointly estimate the GDP growth and factors at the quarterly frequency. The consideration is again that GDP data are released with significant delay. By separately forecasting the factors using monthly data, we can use more recent information and then incorporate this information in estimating the quarterly GDP growth.

3. Data

Our data cover 74 countries which together account for 93 percent of total U.S. exports in 2017. The data have been retrieved using Haver Analytics and are from the European Commission, Now-Casting Economics, IHS Markit, Wolters Kluwer, and countries' individual central banks and national statistical agencies. We include 9 data categories in total: Blue Chip forecasts, business confidence, consumer confidence, employment, exports, industrial

[2] We constructed foreign GDP growth for advanced economies and for emerging economies. For each country group, we added the GDP levels of all countries with data available and then calculated year-over-year and quarter-over-quarter growth rates.

production, now-cast index, PMI, and private sector credit. We further group them into four categories: (1) “hard” data, which measure real activities that are directly related to total output in a country such as industrial production, (2) “soft” data, which does not directly measure real activities but provides indirect information about the performance of real activities, such as consumer confidence, (3) forecast data, which represents the views from the private sector forecasters which we think may contain extra information about an economy, and (4) PMI data, which is generally considered to be highly correlated with GDP growth. We treat PMI data between hard and soft data as the PMI data is closely related to manufacturing and production activities though it does not directly measure output in an economy. For each data series, we include as many countries as we have data available for, starting in 2000. The details are reported in Table 2.

To provide a timely measure of foreign growth, all selected data used in the factor analysis have a monthly frequency which means that we can provide a monthly measure of foreign growth. There are several issues with these data that need to be solved before any analysis is conducted. First, we notice that some of these data series are very volatile. We therefore apply some treatment to the data. For example, as summarized in Table 3, we use G3, meaning growth rates over the last 3 months (annualized rates) for advanced economies, and G6 for emerging economies for the following data series: IP, employment, exports, and credit levels. We choose G6 for emerging economies because data in those countries is generally more volatile.

We also replace outliers as follows: for our advanced economy growth rate variables (G3, annualized rate), we replace observations greater than the 98th percentile or less than the 2nd percentile with the 98th or 2nd percentile. Since data in emerging economies is usually more volatile, we use 95th and 5th percentile for emerging economies (G6, AR variables). We also replace any growth rate > 50% with 50% and any growth rate < -50% with -50%, except for the period 2008m1 – 2010m12 (financial crisis). That is, we consider the 2007-09 Great Recession an unusual period where economic activities could move widely. In other periods, however, we treat those unusually large observations as errors. Overall, the growth rate data are defined so that for advanced economies:

1) Max value = 98th percentile or 50%

2) Min value = 2nd percentile or -50%

Similarly, for emerging economies:

1) Max value = 95th percentile or 50%

2) Min value = 5th percentile or -50%

Another issue is the missing values or unbalanced data. Since every data series is released at different dates, we have an unbalanced data set at any given date. As explained in the previous section, for those missing data, we forecast them using an AR process with an optimal lag. With the forecasted data, we will have monthly data with only one-month delay. This allows us to capture the most recent development across different foreign countries and provide a timely measure of foreign demand.

4. Results

We present three sets of results in this section. The analysis is based on the data collected on July 5, 2018. To show how the forecasts can be updated over time, we compare the forecasts with the data collected on May 23, 2018. These two dates are about three weeks before two consecutive Federal Open Market Committee (FOMC) meetings. So, the difference represents the new information received during the intermeeting period. In other words, the revision in the foreign growth forecast is due to the new information received in this period (including revisions in the data). This example helps illustrate how the forecasts can be used to show revisions in foreign growth forecasts.

The first set of results show the estimated factors. Figures 1 and 2 show the estimated first factors and their forecasts for advanced and emerging economies respectively. Both are at a monthly frequency. In both figures, the level of the factors is normalized—0 corresponds to the average level and the vertical axis shows the standard deviations from the average. Though both figures show some similarities such as a plunge during the 2007-09 recession, they show different patterns more recently. In particular, the current level of the first factor for advanced economies is above zero while the current level for the emerging economies is below zero. This suggests that growth in advanced economies is above the historical average and growth in emerging economies is below its historical average. The unusual weakness shown in the emerging economies may be due to the structural slowdown in Chinese growth, which has declined from about 11 percent to less than 7 percent since 2011. This also means that going forward, how much of the growth improvement emerging economies can have will be an important determinant of foreign growth. In addition, while it is helpful to know whether the forecast is above or below its historical average, it is as important to know whether the forecast is improving or worsening and whether the forecast is improving or worsening compared to the previous forecast.

Figures 3-6 show the first factors for different types of data (i.e., hard data, soft data, PMI data, and forecast data). For each type of data, we show the first factors for both advanced economies and emerging economies in the same figure so we can better see the differences between the two groups of countries. Figure 3 shows that the first factors of hard data look similar for the two groups of countries—they rose to above-trend levels (i.e. the zero level) in 2017, but have fallen below their trends more recently. Our model predicts they will return to their averages next year (i.e., 2019). Of course, using VARs to forecast the factors means that the forecasts will always return to its historical average. But, it is also important to notice whether the return to average take 1 – 2 years or 3 or more years.

The first factors based on the soft data in Figure 4 indicate above-trend performance for both groups of countries. Interestingly, the performance of emerging economies is relatively stronger than advanced economies, although both are expected to slow in the near term. So the weaker forecast for emerging economies cannot be explained by the soft data.

However, the PMI data in Figure 5 confirms the weakness in emerging economies compared to advanced economies. Furthermore, Figure 6 shows the forecast data is in line with the PMI data pointing to the weakness in the emerging group. Unlike the hard data which shows that the two groups of countries stay close with each other, the forecast data suggests that the advanced economies have been doing better than emerging economies—the first factor for advanced economies has been above the trend over the last one and a half years while the first factor for emerging economies barely reached the average level in 2017 before it went down earlier this year.

Overall, these comparisons confirm that advanced economies have been leading global growth recovery in recent years (i.e., since 2015). They also show that the difference between the two groups of countries can largely be explained by the PMI data and the forecast data, while the dynamics of the hard data for the two groups of countries are very similar and the soft data points to strength in emerging economies.

The second set of results compare the current forecasts (based on data collected on July 5th, 2018) with the previous forecast (based on data collected on May 23rd, 2018). Figures 7 and 8 show the current forecasts (the blue dashed lines) are slightly weaker than the previous forecasts (the green dashed lines) in both advanced economies and emerging economies. In both figures, the green vertical lines separate the data and the May forecasts while the blue vertical lines separate the data and the July forecasts. The fact that the blue solid lines are below green solid lines in the last couple of months suggest that the data is weaker than expected and explains why the current forecasts are weaker than the previous one.[3]

The next question is what data caused the forecasts to be weaker? To help answer this question, Figures 9-12 show forecasts revisions in different types of data in advanced economies. They clearly show that the weaker forecast in advanced economies is mainly driven by weaker-than-expected hard data (Figure 9), while the soft data projection actually became stronger (Figure 10). In addition, the PMI data (Figure 11) and forecast data (Figure 12) also contribute slightly to the weaker forecasts for advanced economies. The explanations for the weaker forecast in emerging economies are quite different, though. Figures 13-16 show that the weaker forecast in emerging economies is mainly driven by the plunge in PMI data (Figure 15) and significantly weaker forecast data (Figure 16), while the hard data (Figure 13) only weakened slightly and the soft data (Figure 14) actually became stronger. It is worth noting that the hard

[3] As we forecasted some data in the May analysis (for those series that were unavailable in May), the fact that the blue solid line is below the green solid line could reflect either the data revisions or the weaker-than-expected incoming data. Here, we call both cases weaker-than-expected data.

data has most data series (as shown in the last column in Table 2) and thus has relatively larger influence on the forecast.

The third set of results show the forecast of foreign GDP growth. As explained in the previous section, our GDP forecasts are based on the forecasts of factors for different groups of countries and the relationship between the factors and GDP growth. In particular, we forecast factors by an optimal AR process for each group of countries (advanced and emerging). The relationship between the GDP growth and factors is captured by an estimated VAR model which includes GDP growth for two groups of countries and the quarterly measures of factors for the two groups of countries. Figures 17-18 show real GDP growth (q/q, annualized rate) and factors (quarterly averages of monthly factors) in the same chart for advanced economies and emerging economies respectively. The solid lines are data and the dashed lines are forecasts. The comparison shows that GDP growth and the estimated factor in general move together, confirming that the factors could be used to forecast GDP growth. It is worth noting that the units are different—it is percent for GDP growth and standard deviation for the factor—thus the magnitude of the variations is different for GDP growth and the corresponding factor. The smoother versions of the two figures (y/y growth) are shown in Figures 19-20.

Finally, the GDP forecasts for the two groups of countries for the current and previous FOMC cycle are shown in Figures 21-22 (in the q/q format) and Figures 23-24 (in the y/y format). The values of the forecasts are shown in Tables 4-7. Take the q/q forecasts for advanced economies in Figure 21 as an example. The blue line shows the data and forecasts for July FOMC cycle (data collected on 7/05/2018) while the green line shows the data and forecasts for June FOMC cycle (data collected on 5/23/2018). The comparison clearly shows that the current forecast of foreign GDP growth is weaker than the previous forecast. This is not surprising given the weaker forecasts we have estimated from underlying factors. In addition, the weakness mainly lies in the near term and the medium-term forecast is largely unchanged. This is also true if we compare the y/y forecasts. For emerging economies, the current q/q forecast is largely unchanged from the previous one (Figure 22). However, using the y/y format, it is slightly stronger in the near term, as shown in Figure 24.

5. Conclusions

Having a timely measure of foreign economic growth is important to a lot of economic analysis. One example is forecasting export growth. Taking the U.S. as an example, the demand for U.S. goods and services depends on the strength of foreign countries. When foreign economic growth is high, it is likely their demand for U.S. goods and services is strong and vice versa. However, GDP, the main measure of economic growth in a country, is released with a significant delay. In most countries, it is released with a delay of 1-2 quarters. Lack of a timely measure of foreign growth makes any analysis relying on a timely measure of GDP growth very difficult. We therefore use monthly data from 74 countries (which account for more than 90 percent of U.S. exports) to construct a monthly measure of foreign growth. This monthly measure helps gauge foreign economic development and forecasts U.S. export growth in a timely manner. Our framework is flexible to include any monthly indicators that are informative about economic growth in a given country/region. In addition, though our primary goal is to construct a timely measure of foreign GDP growth to help forecast U.S. export growth, the analysis can be applied to study economic growth in different regions.

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Table 1: Availability of Different Data across Countries

Data	Latest Month Available (as of July 5, 2018)		
	June	May	April
Employment	AUT	AUS, CAN, DEU, FIN, HKG, HRV, JPN, KOR, LUX, MAC, RUS, SWE, TWN	BGR*, GBR*, KGZ, NOR, ROU
Exports	BRA, ISL, KOR	ARG, ARM, AUS, BIH, CHE, CHL, CHN, COL, CRI, HKG, IDN, IND, ISR, JPN, LBN, LUX, MEX, MYS, NOR, NZL, PAK, PRY, SGP, SLV, SWE, THA, TUR, TWN, UGA, URY	AUT*, BEL, BGR, CAN, CZE, DEU, DNK, ECU, EGY, ESP, EST, FIN, FRA, GBR, HRV*, HUN, IRL, IRN**, ITA, KAZ*, KGZ, LTU, LUX, LVA, MLT, NLD, PER, PHL, POL, PRT, ROU, RUS, SVN*, UKR
Industrial production	.	CHN, ESP, EST, HRV, IRL, JPN, KAZ, KOR, LTU, LVA, POL, RUS, SRB, SWE	AUT, BEL, BGR, CAN, CYP, CZE, DEU, DNK, FIN, FRA, GBR, GRC, HUN, IND, ITA, LUX, MLT, MYS, NLD, NOR, ROU, SVK, SVN, TUN, TUR
Private sector credit	.	AUS, BGR, BIH, BRA, CAN, CHE, DNK, EST, FRA, GBR, GEO, GRC, GTM, HKG, HRV, HUN, IDN, KAZ, LTU, MAC, MYS, NLD, NOR, NZL, POL, SGP, TWN, ZAF	IND, IRL, ITA, KOR
Business confidence	BEL, CHE, DEU, DNK, FRA, HUN, NLD, POL, SVK, SVN, SWE, THA	.	.

Consumer confidence	AUS, AUT, BEL, CHE, CZE, DEU, DEV, DNK, ERU, ESP, FIN, FRA, GBR, GRC, HUN, IRL, ITA, JPN, NLD, POL, PRT, RUS, SVK, SVN, SWE	BRA, CHN, LUX	.
Blue Chip GDP forecasts	AUS, BRA, CAN, CHN, DEU, FRA, GBR, HKG, JPN, KOR, MEX, NLD, TWN	.	.
Now-cast index	BRA, CHN, GBR, MEX, ZAF	.	.
PMI	HUN, NLD, SGP, SVN, SWE, ZAF	ISR	

Notes:
*Latest available data is actually from March
**Latest available data is actually from February

Table 2: Data Categories

Series	Data Type	Countries	Number of Data Series
Employment	Hard	AUS, AUT, BGR, CAN, DEU, FIN, GBR, HKG, HRV, JPN, KGZ, KOR, LUX, MAC, NOR, ROU, RUS, SWE, TWN, VEN	132
Exports	Hard	ARG, AUS, AUT, BEL, BRA, CAN, CHE, CHL, CHN, COL, DEU, DNK, EGY, ESP, FIN, FRA, GBR, HKG, IDN, IND, IRL, ISL, ISR, ITA, JPN, KAZ, KOR, LUX, MEX, MLT, MYS, NLD, PAK, PER, PHL, POL, ROU, RUS, SGP, TUR	
Industrial production	Hard	ARG, AUT, BEL, BGR, CAN, CHN, CYP, CZE, DEU, DNK, ESP, EST, FIN, FRA, GBR, GRC, HRV, HUN, IND, IRL, ITA, JPN, KAZ, KOR, LTU, LUX, LVA, MLT, MYS, NLD, NOR, POL, ROU, RUS, SRB, SVK, SVN, SWE, TUN, TUR	
Private sector credit	Hard	AUS, BGR, BIH, BRA, CAN, CHE, DNK, EST, FRA, GBR, GEO, GRC, GTM, HKG, HRV, HUN, IDN, IND, IRL, ITA, KAZ, KOR, LTU, MAC, MYS, NLD, NOR, NZL, POL, SGP, TWN, ZAF	
Business confidence	Soft	BEL, CHE, DEU, DNK, FRA, HUN, NLD, POL, SVK, SVN, SWE, THA	35
Consumer confidence	Soft	AUS, AUT, BEL, BRA, CHN, CZE, DEU, DNK, ESP, FIN, FRA, GBR, GRC, HUN, IRL, ITA, JPN, LUX, NLD, PRT, SVK, SVN, SWE	
Blue Chip GDP forecasts	Forecast	AUS, BRA, CAN, CHN, DEU, FRA, GBR, HKG, JPN, KOR, MEX, NLD, TWN	19
Now-cast index	Forecast	BRA, CHN, GBR, JPN, MEX, ZAF	
PMI	PMI	AUT, CHE, DEU, DNK, ESP, FRA, GBR, GRC, HUN, IRL, ISR, ITA, NLD, POL, RUS, SGP, SVN, SWE, ZAF	19

Table 3: Data Treatment

Transformation	Data series
G3 (annualized growth rate over last 3 months)	IP, employment, exports, credit (adv economies only)
max value = 98th percentile, min value = 2nd percentile	IP, employment, exports, credit (adv economies only)
G6 (annualized growth rate over last 6 months)	IP, employment, exports, credit (emerg economies only)
max value = 95th percentile, min value = 5th percentile	IP, employment, exports, credit (emerg economies only)
replace values>50% with 50%, replace values<-50% with -50%*	IP, employment, exports, credit

*Note: We do not do this during the financial crisis (January 2008-December 2010)

Table 4: Real GDP q/q Growth Forecasts, Current and Previous FOMC Cycles (Advanced Economies)

	Actual		Predicted	
date	Current	Previous	Current	Previous
2015q1	3.17	3.10	3.17	3.10
2015q2	1.01	1.01	1.01	1.01
2015q3	1.84	1.85	1.84	1.85
2015q4	1.19	1.20	1.19	1.20
2016q1	2.50	2.41	2.50	2.41
2016q2	1.27	1.50	1.27	1.50
2016q3	1.51	1.50	1.51	1.50
2016q4	2.49	2.40	2.49	2.40
2017q1	2.66	2.63	2.66	2.63
2017q2	2.64	2.64	2.64	2.64
2017q3	2.62	2.62	2.62	2.62
2017q4	2.06	1.91	2.06	1.91
2018q1	1.56	.	1.56	2.09
2018q2	.	.	1.76	1.85
2018q3	.	.	0.80	1.05
2018q4	.	.	0.99	1.03
2019q1	.	.	1.21	1.18
2019q2	.	.	1.44	1.39
2019q3	.	.	1.59	1.52
2019q4	.	.	1.63	1.59
2020q1	.	.	1.62	1.61
2020q2	.	.	1.61	1.60
2020q3	.	.	1.60	1.60
2020q4	.	.	1.60	1.60
2021q1	.	.	1.60	1.60
2021q2	.	.	1.59	1.59
2021q3	.	.	1.59	1.59
2021q3	.	.	1.59	1.58
2021q3	.	.	1.59	.

Table 5: Real GDP q/q Growth Forecasts, Current and Previous FOMC Cycles (Emerging Economies)

	Actual		Predicted	
date	Current	Previous	Current	Previous
2015q1	3.14	2.95	3.14	2.95
2015q2	4.02	4.01	4.02	4.01
2015q3	4.19	4.44	4.19	4.44
2015q4	3.76	3.55	3.76	3.55
2016q1	4.15	4.47	4.15	4.47
2016q2	4.19	4.14	4.19	4.14
2016q3	3.77	3.44	3.77	3.44
2016q4	5.31	5.14	5.31	5.14
2017q1	5.42	5.94	5.42	5.94
2017q2	5.38	5.32	5.38	5.32
2017q3	5.20	5.04	5.20	5.04
2017q4	4.63	3.90	4.63	3.90
2018q1	5.91	.	5.91	5.82
2018q2	.	.	6.83	7.17
2018q3	.	.	4.55	4.65
2018q4	.	.	3.52	3.52
2019q1	.	.	5.72	5.65
2019q2	.	.	6.74	6.65
2019q3	.	.	5.35	5.31
2019q4	.	.	4.82	4.84
2020q1	.	.	5.80	5.83
2020q2	.	.	6.10	6.06
2020q3	.	.	5.46	5.42
2020q4	.	.	5.37	5.38
2021q1	.	.	5.83	5.84
2021q2	.	.	5.85	5.82
2021q3	.	.	5.56	5.54
2021q3	.	.	5.59	5.60
2021q3	.	.	5.80	.

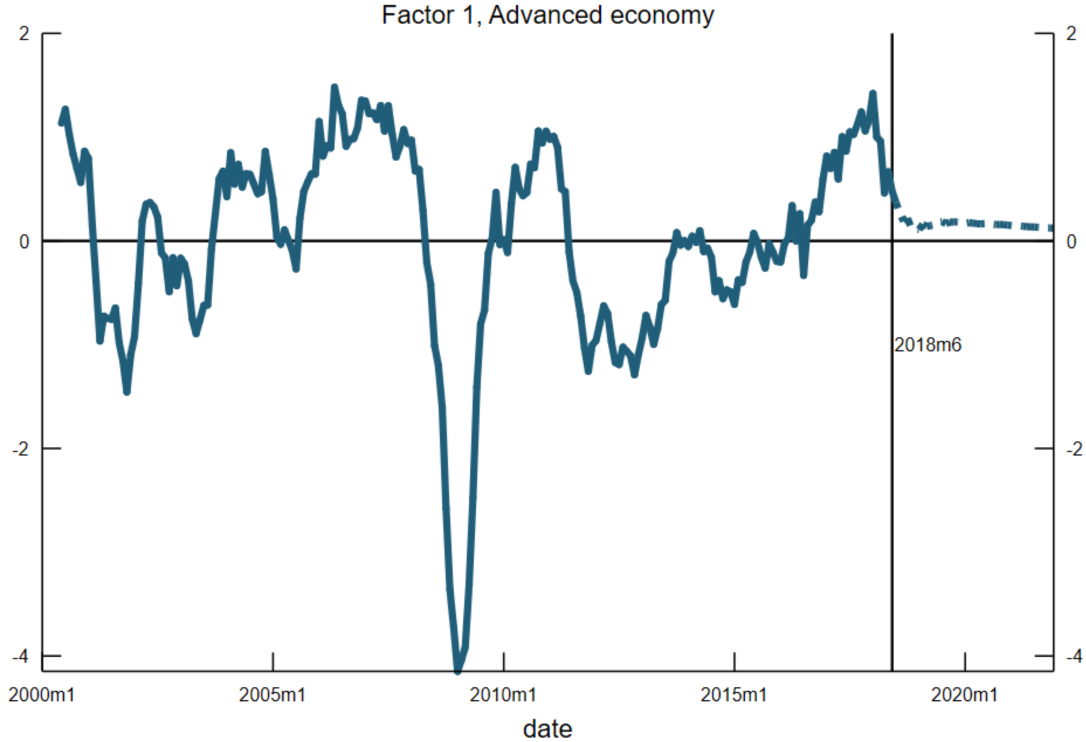
Table 6: Real GDP y/y Growth Forecasts, Current and Previous FOMC Cycles (Advanced Economies)

	Actual		Predicted	
date	Current	Previous	Current	Previous
2015q1	1.78	1.80	1.79	1.80
2015q2	2.05	2.07	2.05	2.07
2015q3	2.09	2.08	2.09	2.08
2015q4	1.80	1.79	1.80	1.79
2016q1	1.64	1.62	1.64	1.62
2016q2	1.70	1.74	1.70	1.74
2016q3	1.62	1.65	1.62	1.65
2016q4	1.94	1.95	1.94	1.95
2017q1	1.98	2.01	1.98	2.01
2017q2	2.32	2.29	2.32	2.29
2017q3	2.60	2.58	2.60	2.58
2017q4	2.50	2.45	2.50	2.45
2018q1	2.22	.	2.22	2.31
2018q2	.	.	2.00	2.12
2018q3	.	.	1.55	1.72
2018q4	.	.	1.28	1.50
2019q1	.	.	1.19	1.28
2019q2	.	.	1.11	1.16
2019q3	.	.	1.31	1.28
2019q4	.	.	1.47	1.42
2020q1	.	.	1.57	1.53
2020q2	.	.	1.61	1.58
2020q3	.	.	1.61	1.60
2020q4	.	.	1.61	1.60
2021q1	.	.	1.60	1.60
2021q2	.	.	1.60	1.60
2021q3	.	.	1.59	1.59
2021q3	.	.	1.59	1.59
2021q3	.	.	1.59	.

Table 7: Real GDP y/y Growth Forecasts, Current and Previous FOMC Cycles (Emerging Economies)

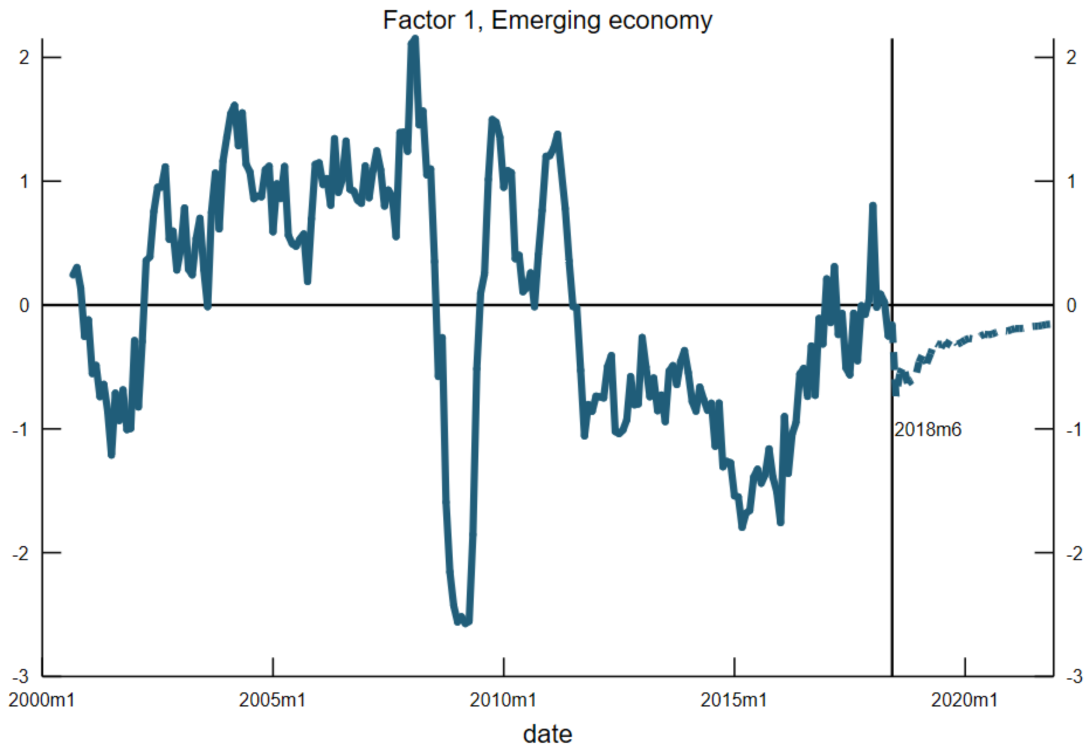
	Actual		Predicted	
date	Current	Previous	Current	Previous
2015q1	4.23	4.20	4.23	4.20
2015q2	4.07	4.04	4.07	4.05
2015q3	3.96	3.97	3.96	3.97
2015q4	3.78	3.74	3.78	3.74
2016q1	4.03	4.12	4.03	4.12
2016q2	4.07	4.15	4.07	4.15
2016q3	3.97	3.90	3.97	3.90
2016q4	4.35	4.30	4.35	4.30
2017q1	4.67	4.66	4.67	4.66
2017q2	4.97	4.96	4.97	4.96
2017q3	5.33	5.36	5.33	5.36
2017q4	5.16	5.05	5.16	5.05
2018q1	5.28	.	5.28	5.02
2018q2	.	.	5.64	5.48
2018q3	.	.	5.48	5.38
2018q4	.	.	5.20	5.29
2019q1	.	.	5.16	5.25
2019q2	.	.	5.13	5.12
2019q3	.	.	5.34	5.28
2019q4	.	.	5.66	5.61
2020q1	.	.	5.68	5.66
2020q2	.	.	5.52	5.51
2020q3	.	.	5.54	5.54
2020q4	.	.	5.68	5.67
2021q1	.	.	5.69	5.68
2021q2	.	.	5.63	5.62
2021q3	.	.	5.65	5.65
2021q3	.	.	5.71	5.70
2021q3	.	.	5.70	.

Figure 1: Factor 1 (Advanced Economies)



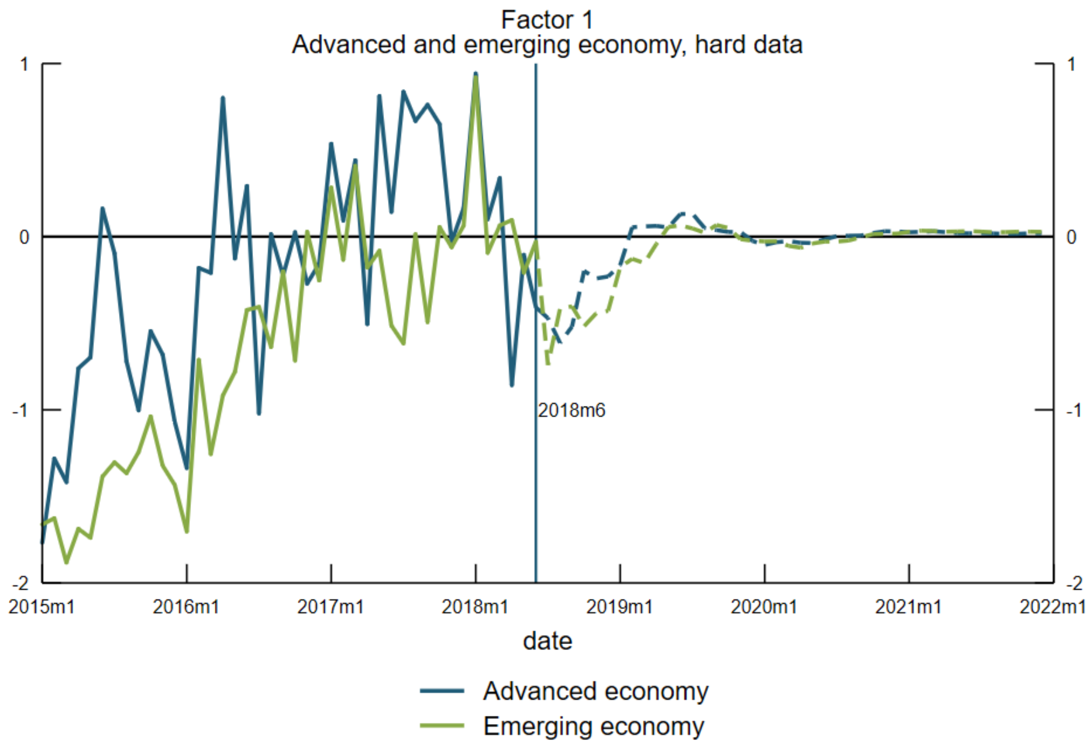
Source: Authors' calculations

Figure 2: Factor 1 (Emerging Economies)



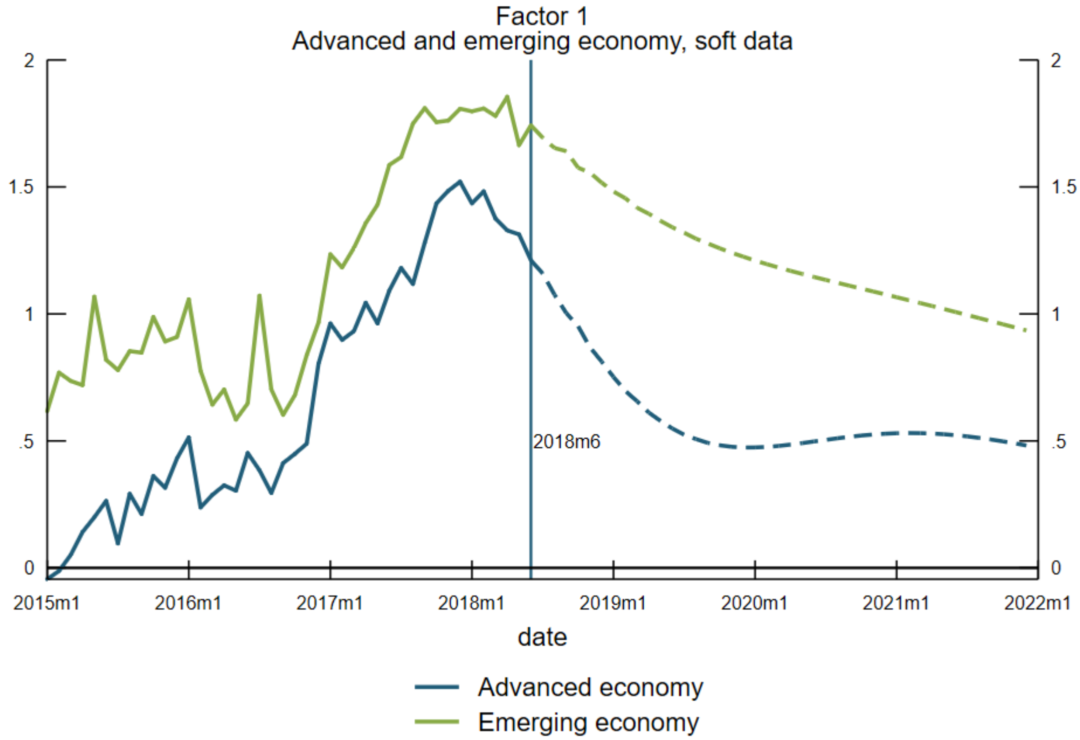
Source: Authors’ calculations

Figure 3: Factor 1, Hard Data (Advanced and Emerging Economies)



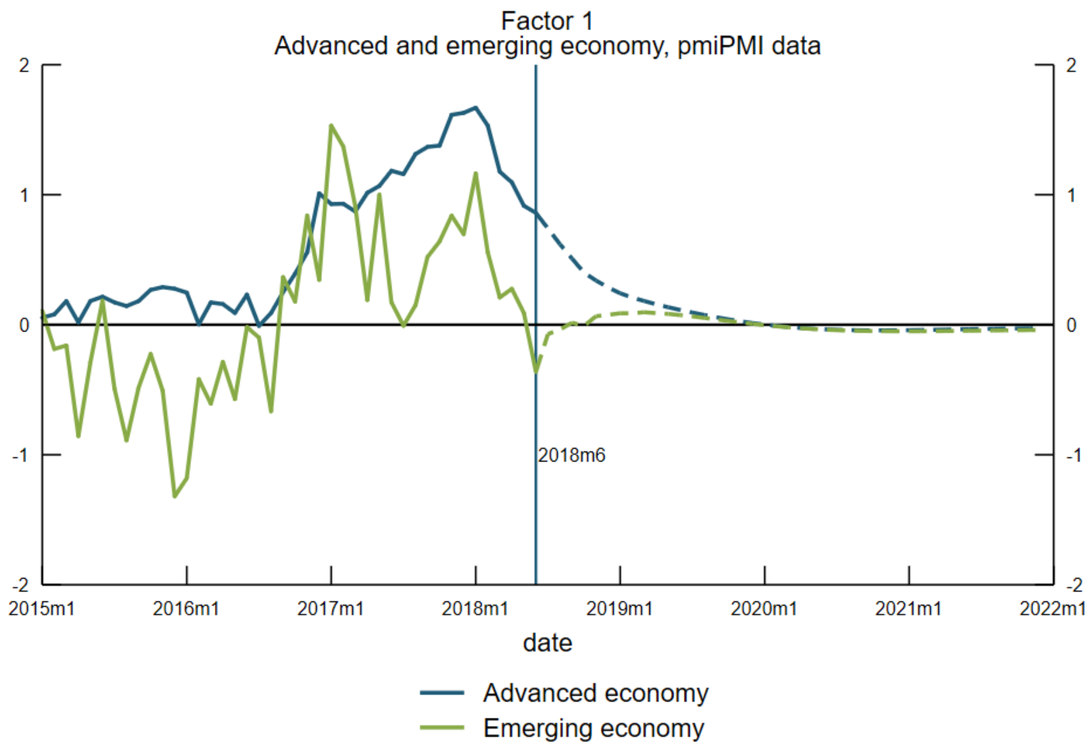
Source: Authors' calculations

Figure 4: Factor 1, Soft Data (Advanced and Emerging Economies)



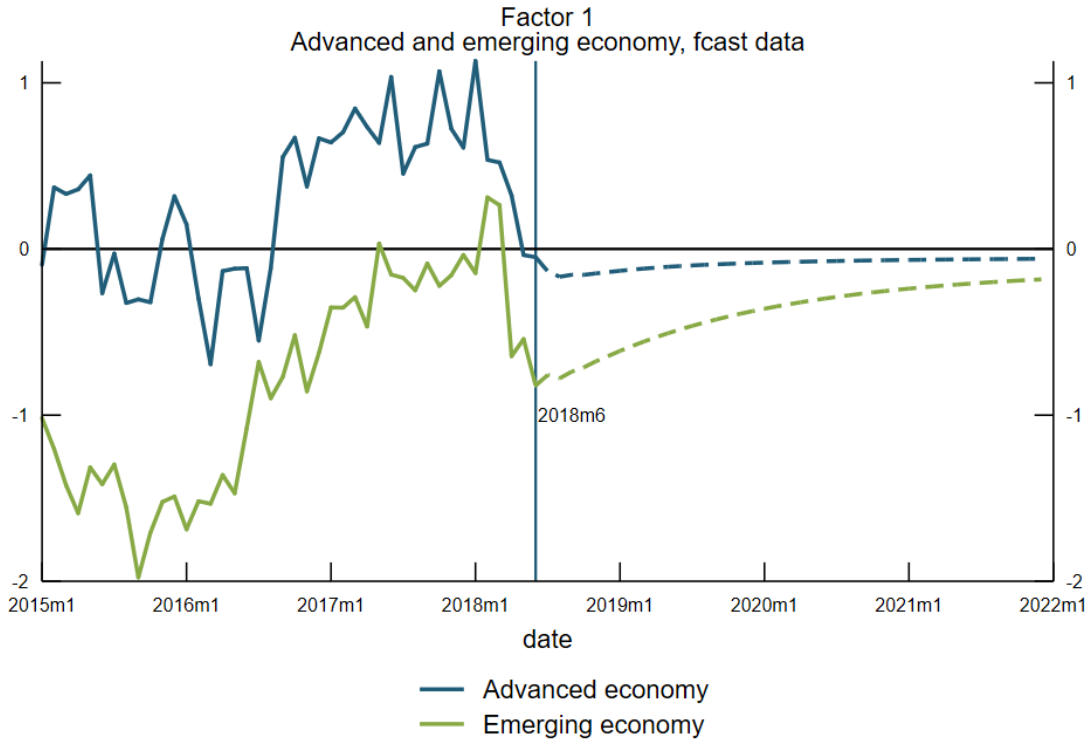
Source: Authors' calculations

Figure 5: Factor 1, PMI Data (Advanced and Emerging Economies)



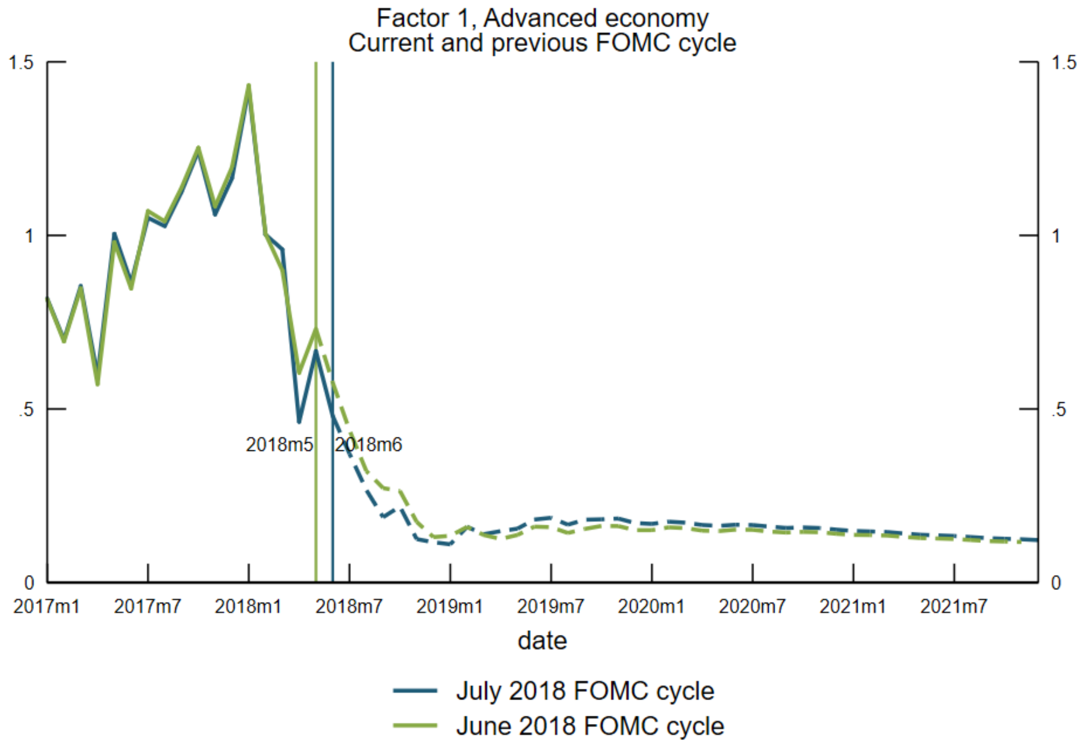
Source: Authors' calculations

Figure 6: Factor 1, Forecast Data (Advanced and Emerging Economies)



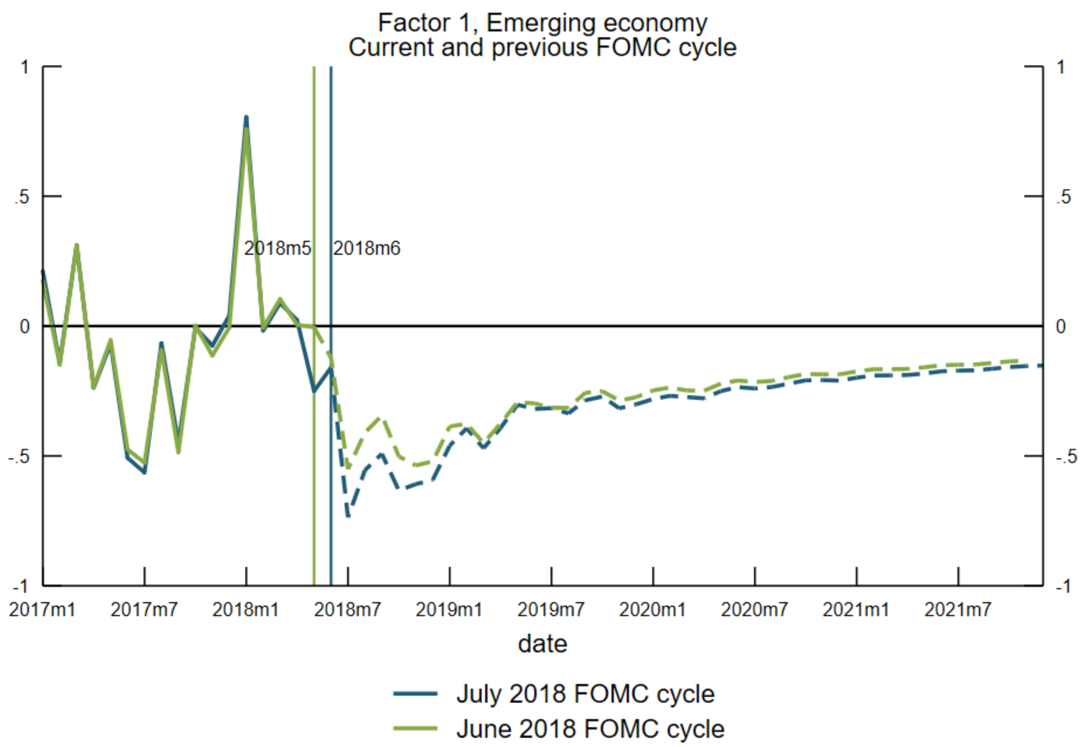
Source: Authors' calculations

Figure 7: Factor 1, Current and Previous FOMC Cycles (Advanced Economies)



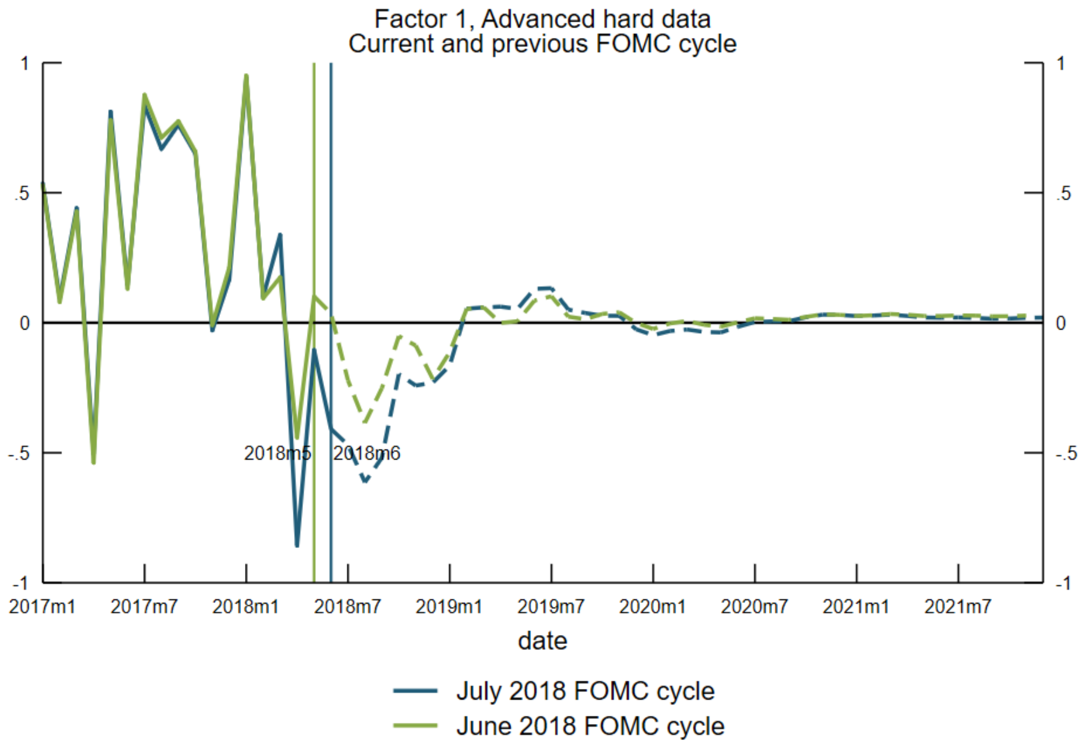
Source: Authors' calculations

Figure 8: Factor 1, Current and Previous FOMC Cycles (Emerging Economies)



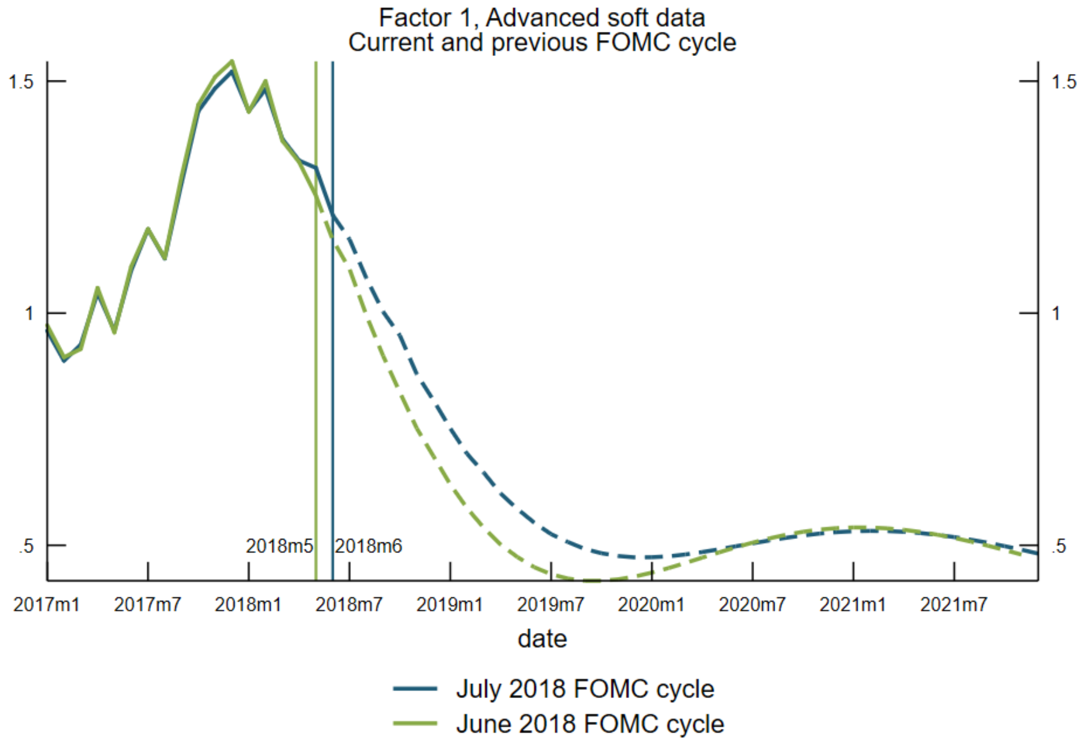
Source: Authors' calculations

Figure 9: Factor 1, Current and Previous FOMC Cycles, Hard Data (Advanced Economies)



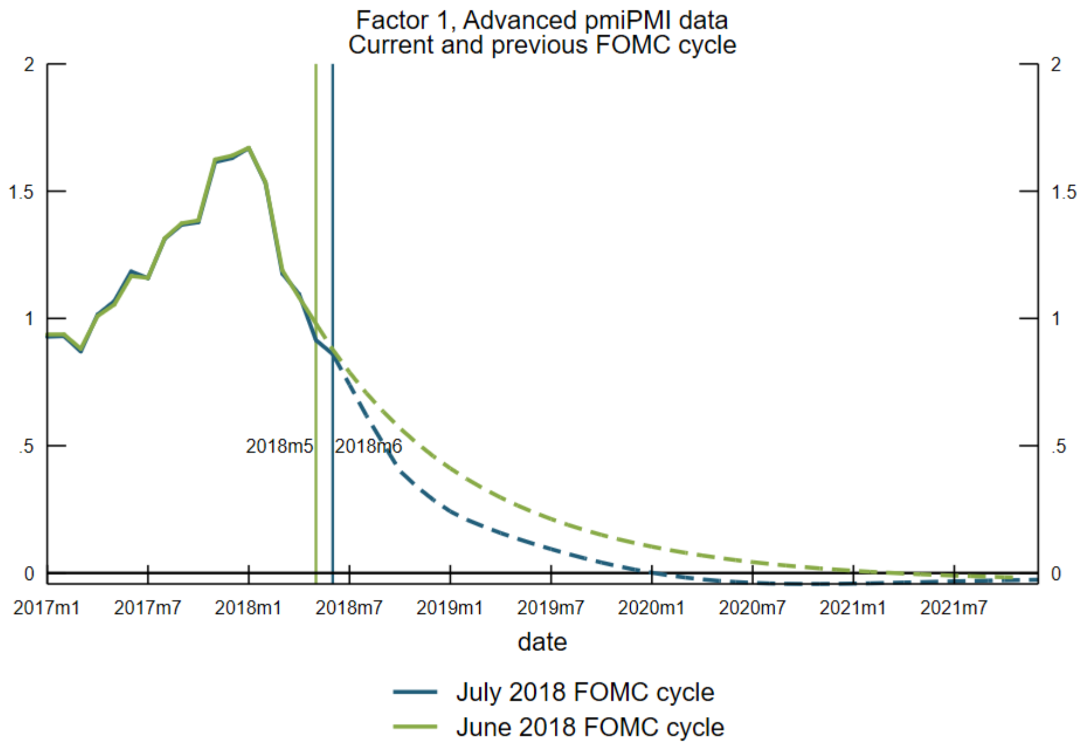
Source: Authors' calculations

Figure 10: Factor 1, Current and Previous FOMC Cycles, Soft Data (Advanced Economies)



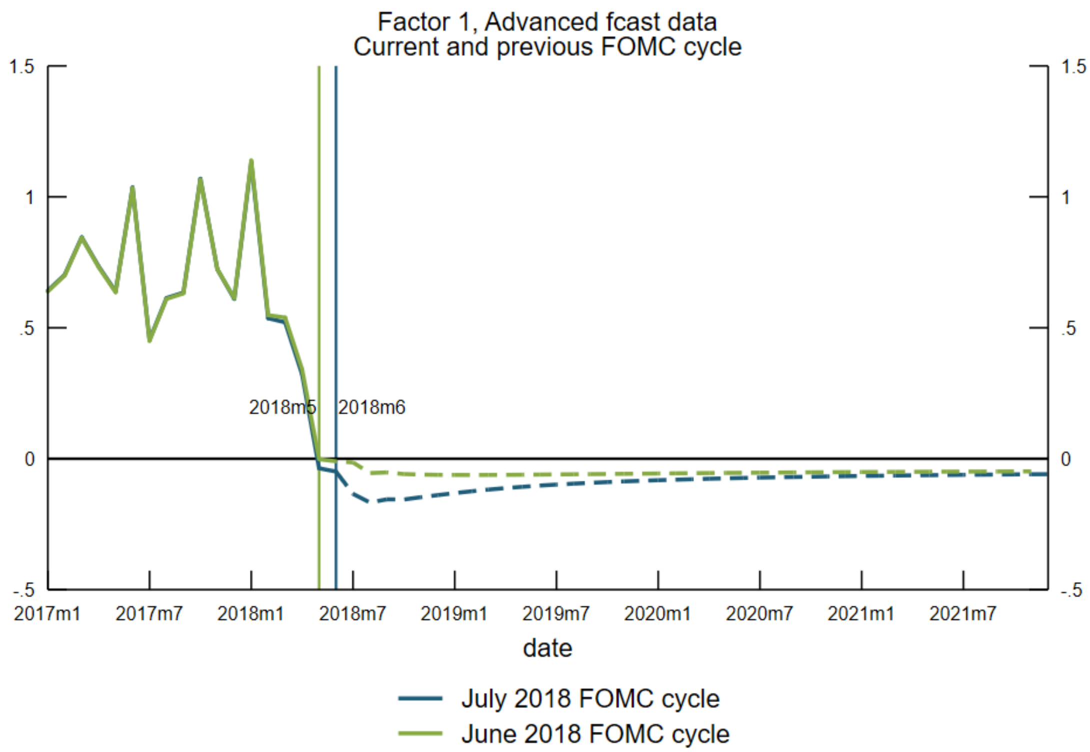
Source: Authors' calculations

Figure 11: Factor 1, Current and Previous FOMC Cycles, PMI Data (Advanced Economies)



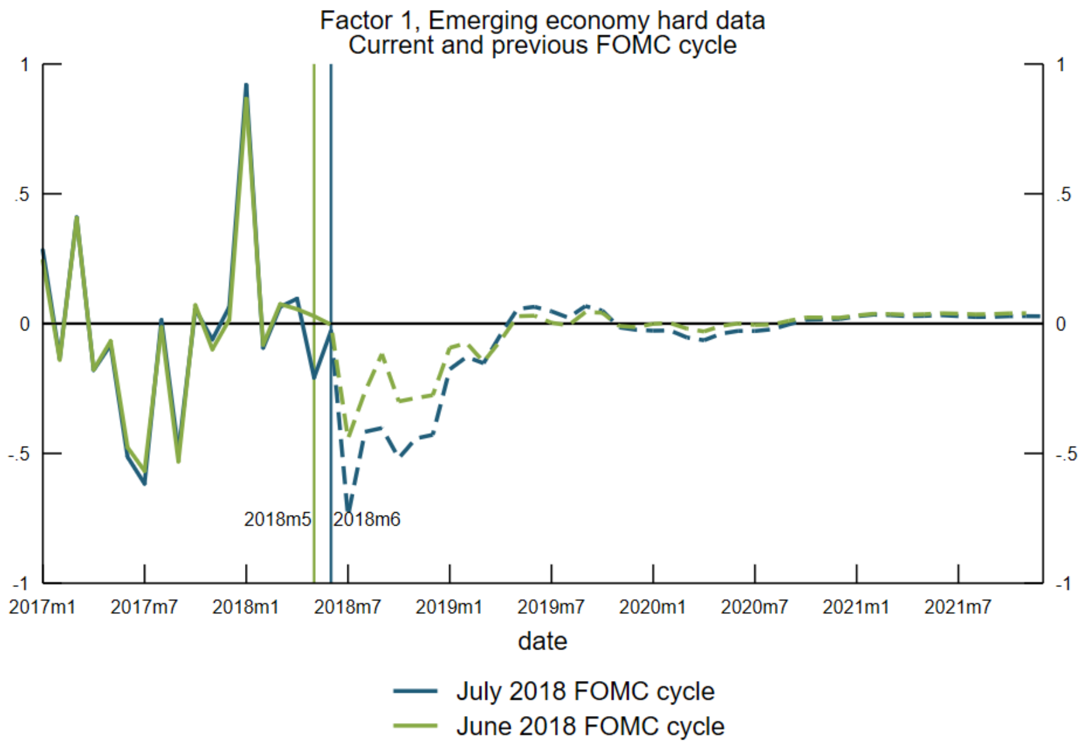
Source: Authors' calculations

Figure 12: Factor 1, Current and Previous FOMC Cycles, Forecast Data (Advanced Economies)



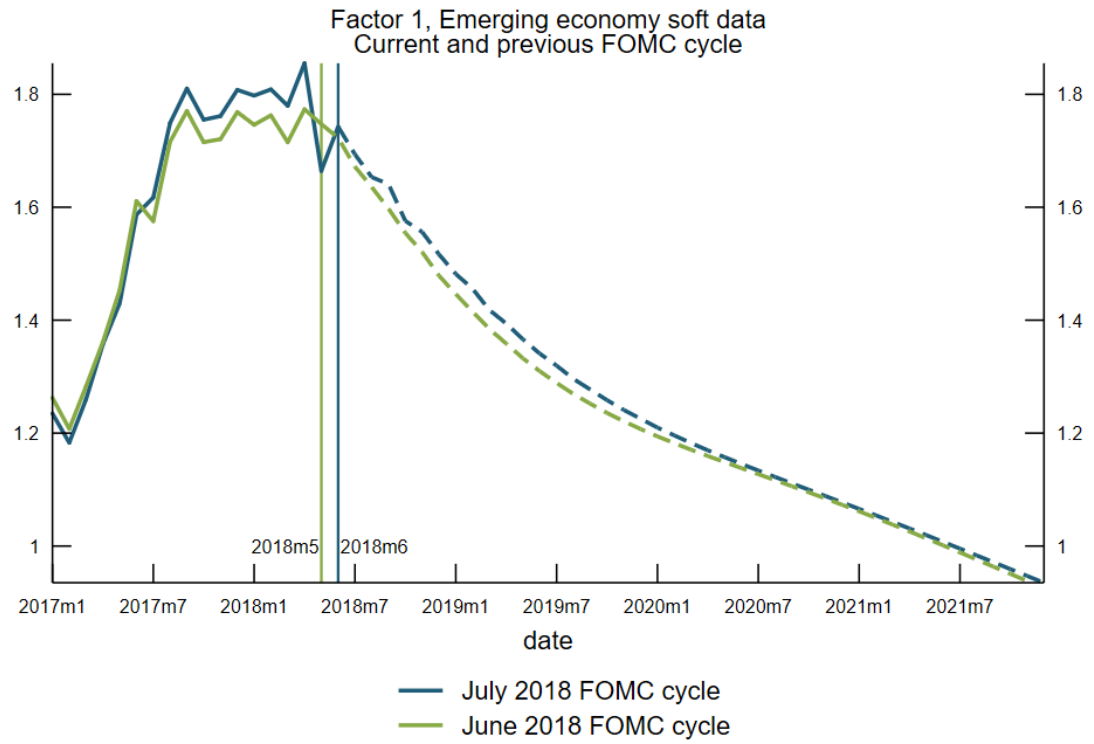
Source: Authors' calculations

Figure 13: Factor 1, Current and Previous FOMC Cycles, Hard Data (Emerging Economies)



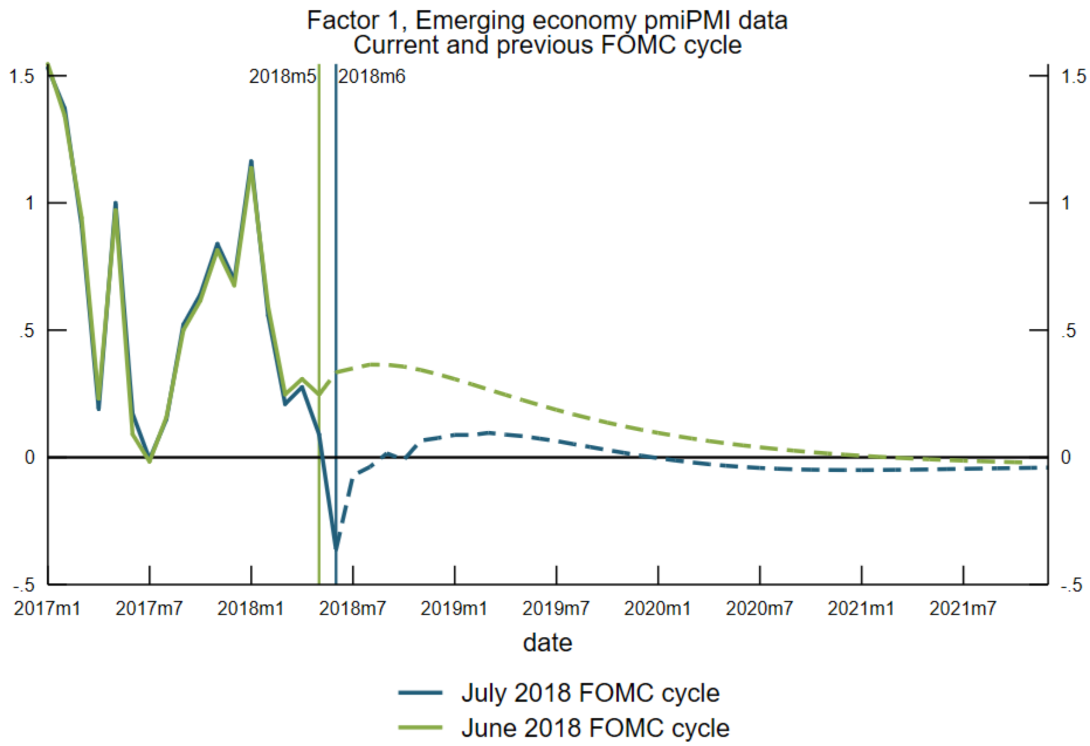
Source: Authors' calculations

Figure 14: Factor 1, Current and Previous FOMC Cycles, Soft Data (Emerging Economies)



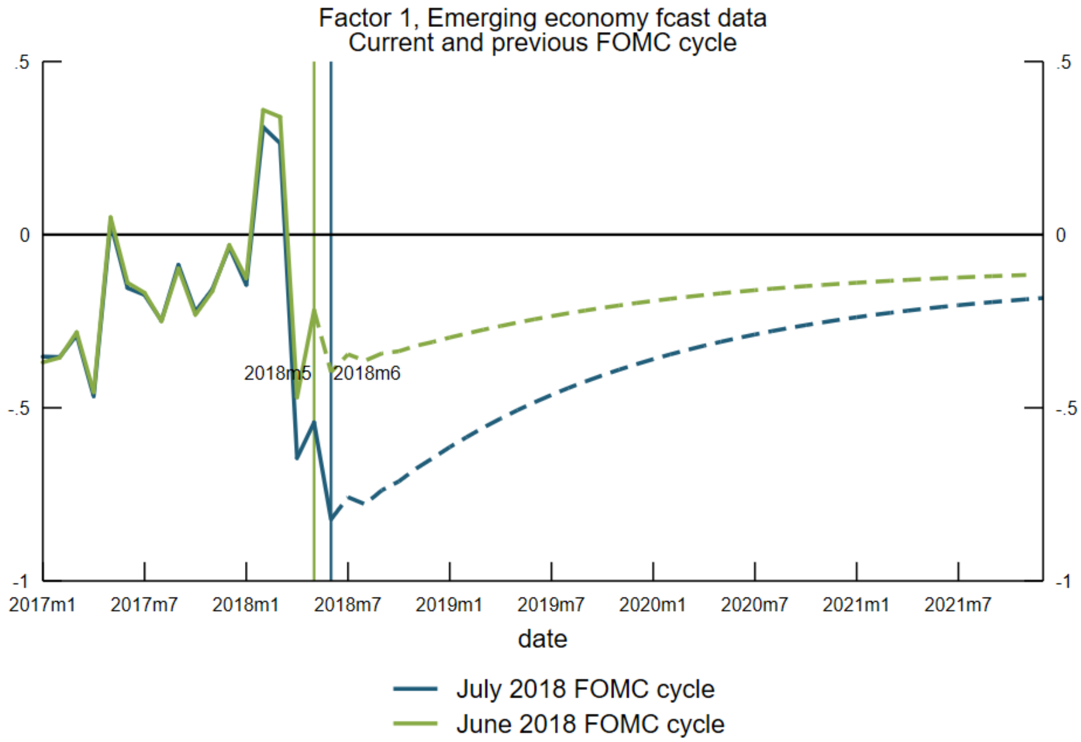
Source: Authors' calculations

Figure 15: Factor 1, Current and Previous FOMC Cycles, PMI Data (Emerging Economies)



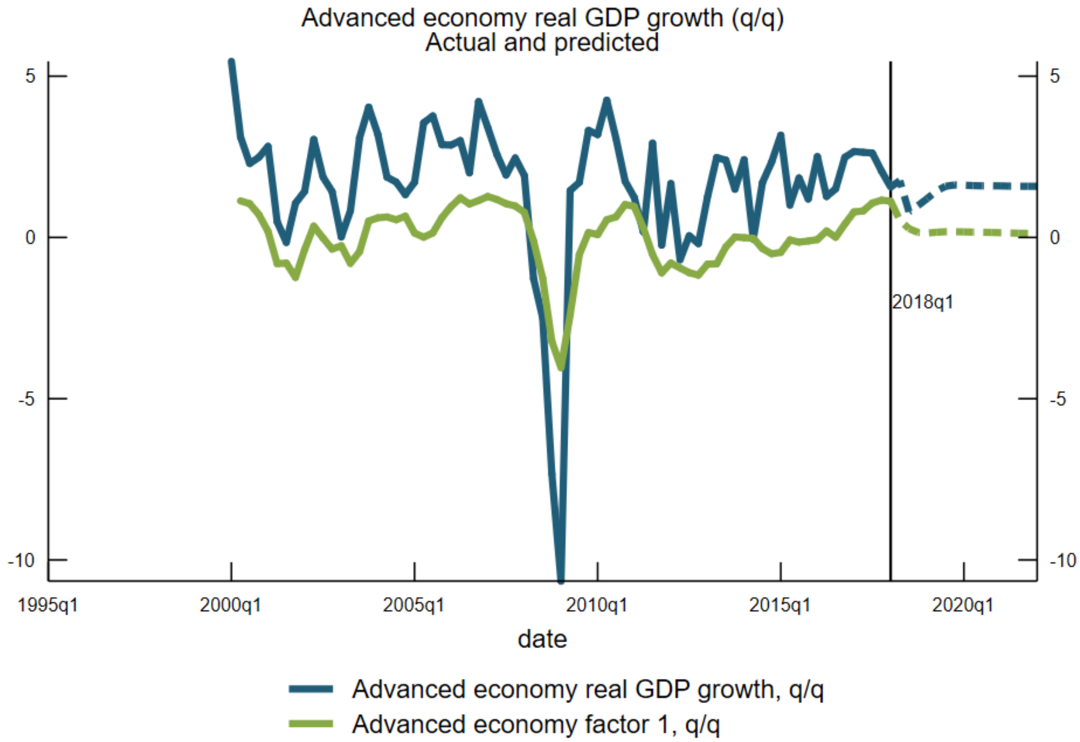
Source: Authors' calculations

Figure 16: Factor 1, Current and Previous FOMC Cycles, Forecast Data (Emerging Economies)



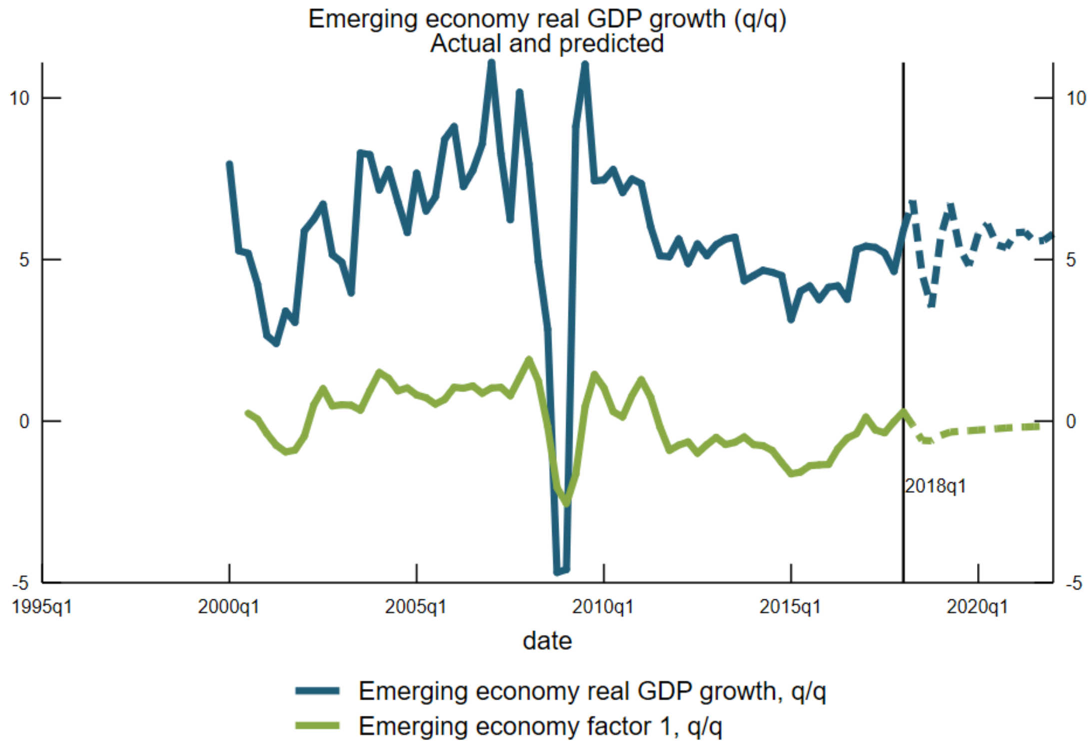
Source: Authors' calculations

Figure 17: Real GDP q/q Growth (Advanced Economies)



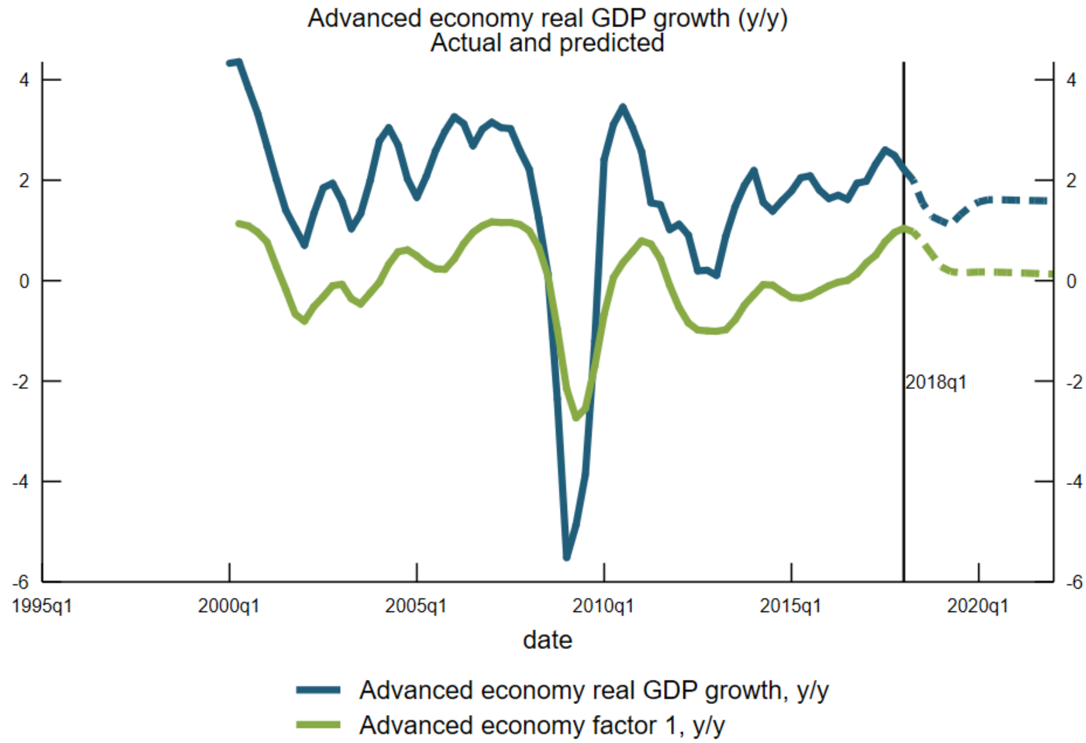
Source: Authors' calculations

Figure 18: Real GDP q/q Growth (Emerging Economies)



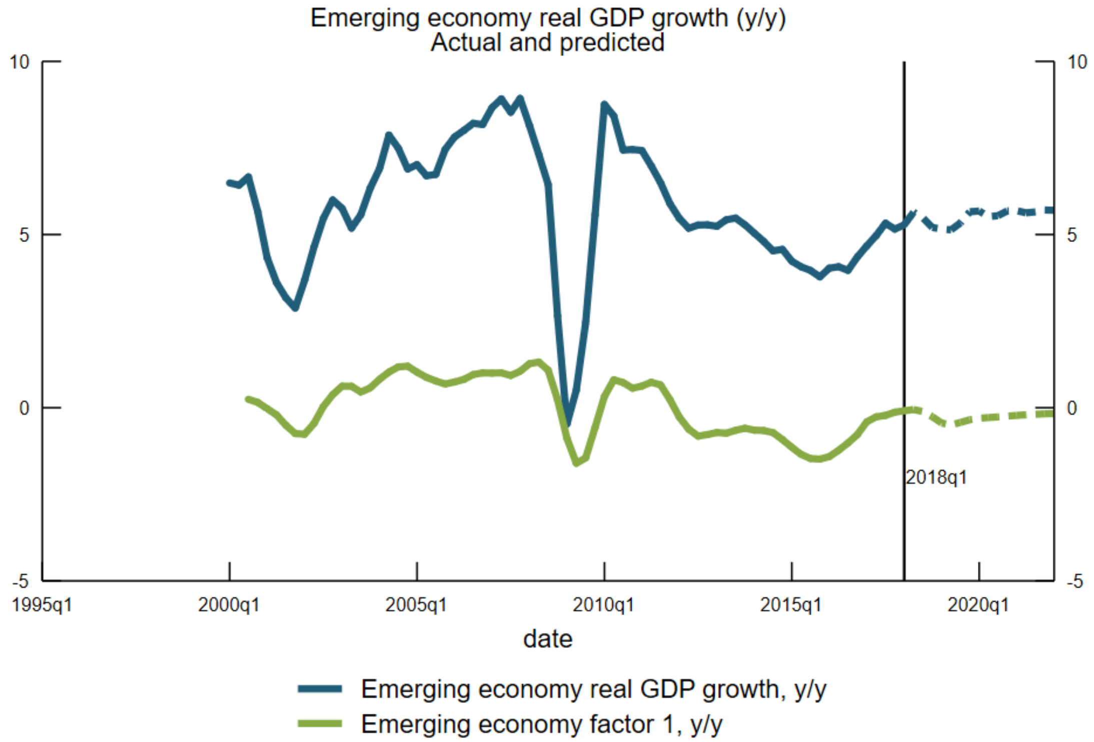
Source: Authors' calculations

Figure 19: Real GDP y/y Growth (Advanced Economies)



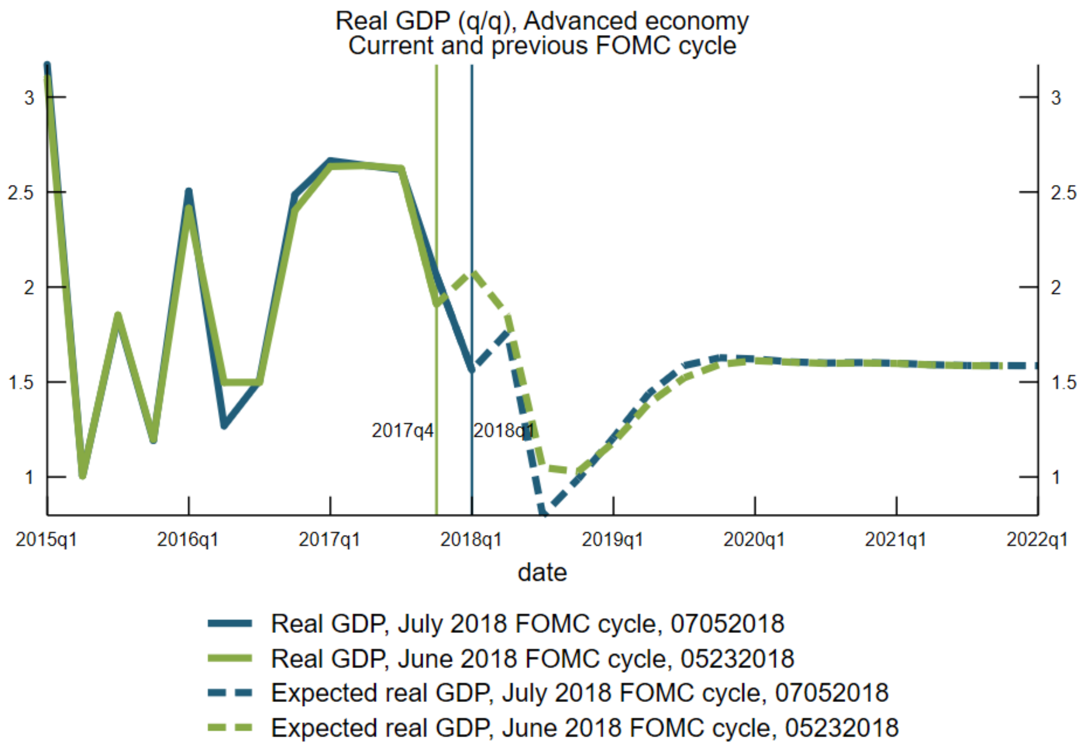
Source: Authors' calculations

Figure 20: Real GDP y/y Growth (Emerging Economies)



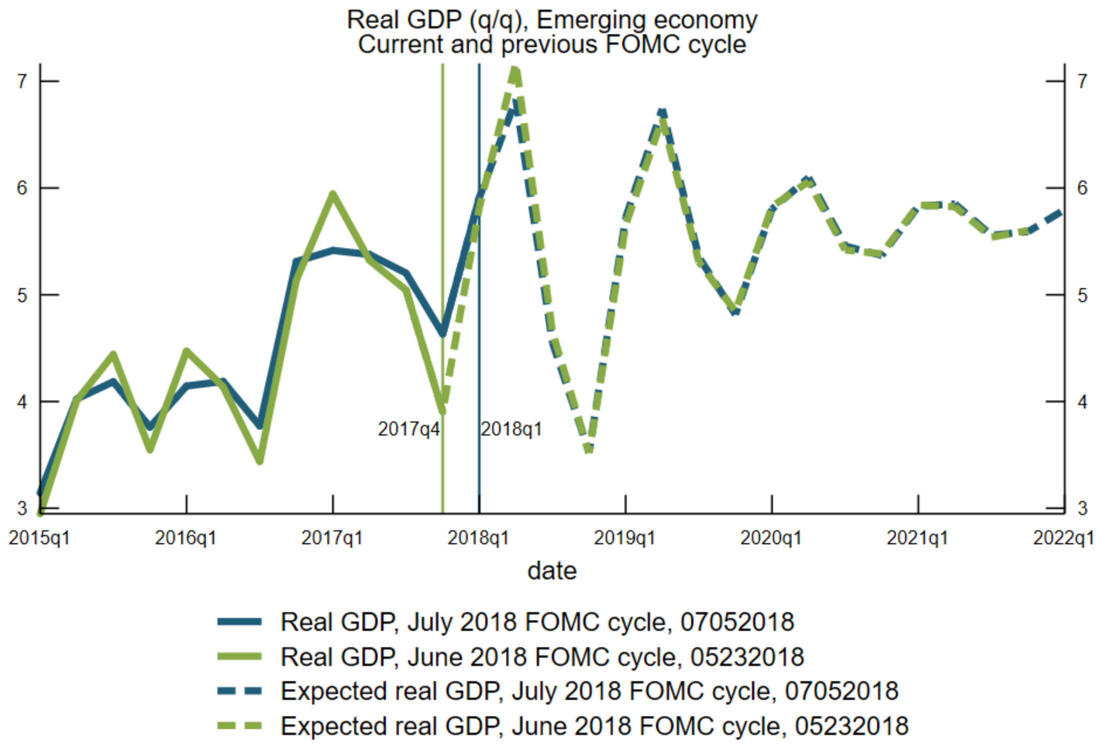
Source: Authors' calculations

Figure 21: Real GDP q/q Growth, Current and Previous FOMC Cycles (Advanced Economies)



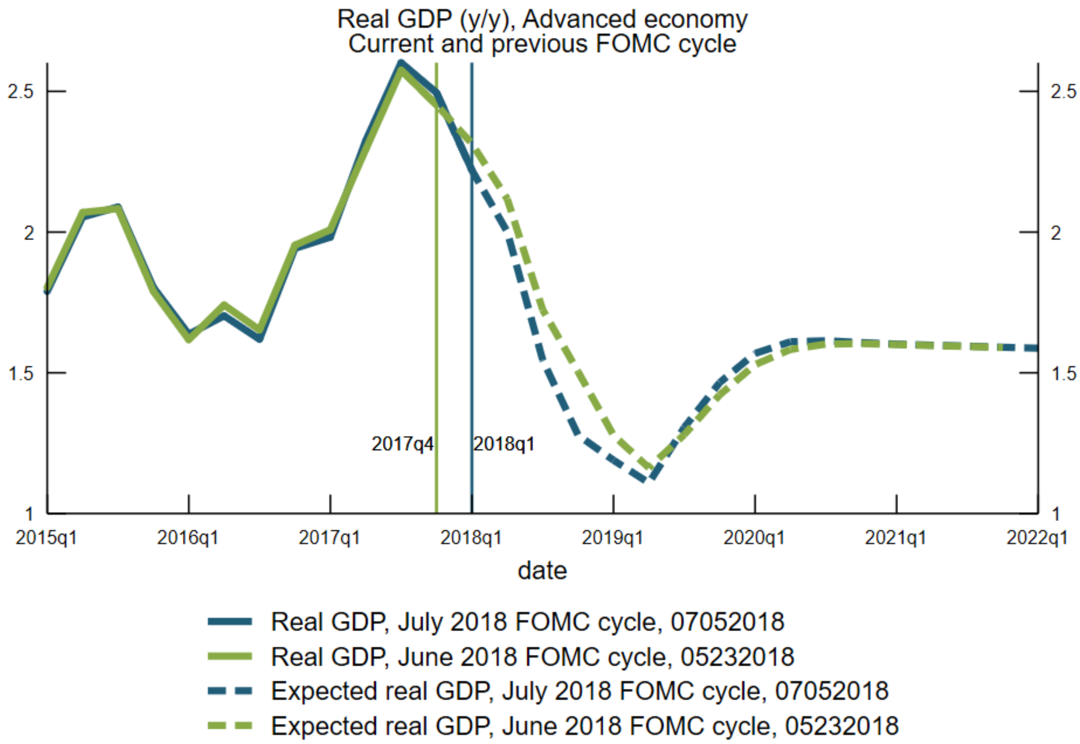
Source: Authors' calculations

Figure 22: Real GDP q/q Growth, Current and Previous FOMC Cycles (Emerging Economies)



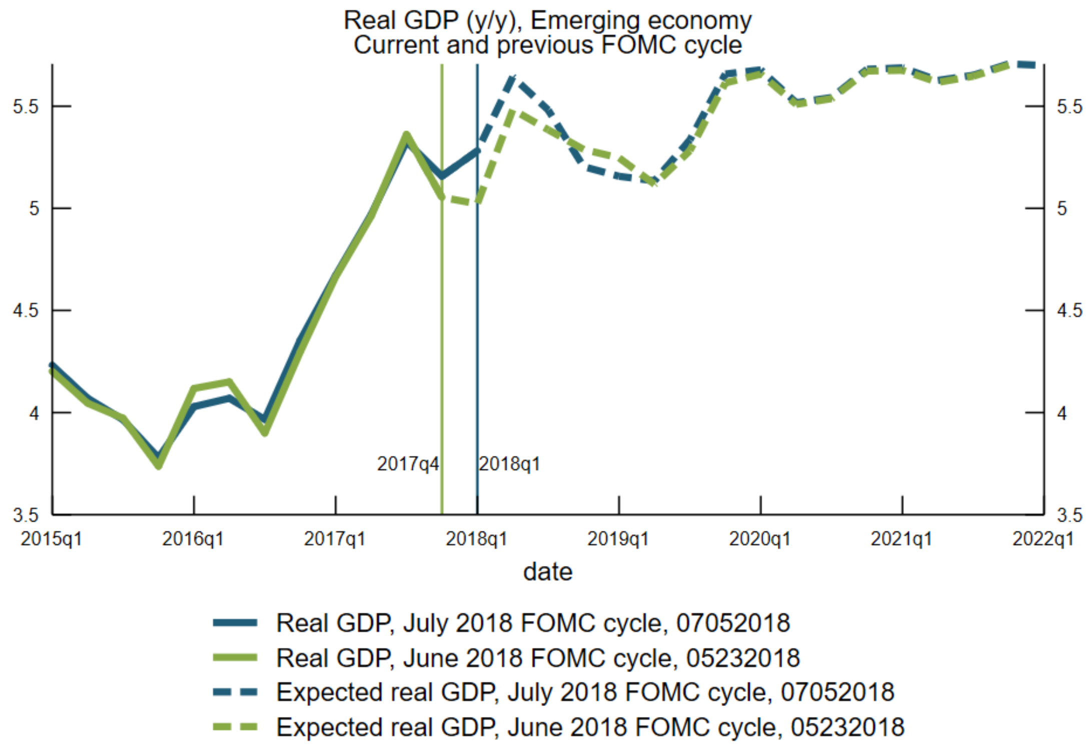
Source: Authors' calculations

Figure 23: Real GDP y/y Growth, Current and Previous FOMC Cycles (Advanced Economies)



Source: Authors' calculations

Figure 24: Real GDP y/y Growth, Current and Previous FOMC Cycles (Emerging Economies)



Source: Authors' calculations