

The NY Fed DGSE model: A Post-Covid Assessment

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Abstract

We document the real-time forecasting performance of the New York Fed dynamic stochastic general equilibrium (DSGE) model since 2011. We find the DSGE's accuracy to be comparable to that of private forecasters before Covid, but somewhat worse afterwards.

JEL CLASSIFICATION: E43, E44, C32, C11, C54

KEY WORDS: DSGE Models, Real-time Forecasts, Inflation

*This paper owes much to the many economists and RAs who were at some point part of the NY Fed DSGE Team, and in particular to William Chen, Marc Giannoni, Shlok Goyal, Alissa Johnson, Ethan Matlin, Reza Sarfati, and Andrea Tambalotti. The views expressed in this paper do not necessarily reflect those of the Federal Reserve Bank of New York or the Federal Reserve System. Moreover, recall that the NY Fed DSGE forecast is not an official New York Fed forecast, but only an input to the Research staffs overall forecasting process.

1 Introduction

The implicit promise of Smets and Wouters (2007)’s work was to deliver a structural model that could be reliably used by central banks for understanding and forecasting economic developments, and quantitative policy analysis. Many policy institutions, including the Federal Reserve Bank of New York (NY Fed), followed up on that promise and added DSGEs to their existing suite of models. How did the promise pan out? We address this question by providing evidence on the relative forecasting performance of the NY Fed DSGE model over the past twelve years compared to the average expectation of professional forecasters such as the Blue Chip Economic Indicators (BCEI) consensus and the median Survey of Economic Forecasters (SPF). We find that the forecast accuracy of the NY Fed DSGE model has been by and large comparable to that of professional forecasters for output growth, as discussed in section 2. The model has been less accurate than private forecasters in terms of core PCE inflation forecasts, with most of the gap arising after Covid.

The period considered here presented many challenges to a rather canonical DSGE model,¹ as it featured several unprecedented situations. These include the recovery from the Great Recession with the federal funds rate (FFR) at the zero lower bound (ZLB) and quantitative easing, the change in the monetary policy framework with the advent of average inflation targeting, and most notably the Covid crisis and its aftermath. Section 3 discusses

¹The NY Fed DSGE is a medium-scale DSGE á la Smets and Wouters (2007) with financial frictions as in Bernanke et al. (1999); Christiano et al. (2014), and is described in Del Negro et al. (2015, 2020). The site <https://github.com/FRBNY-DSGE> contains the code and a description of the model and the data used to estimate it. This information is also in the online appendix and contains all the details that were omitted for brevity in the paper.

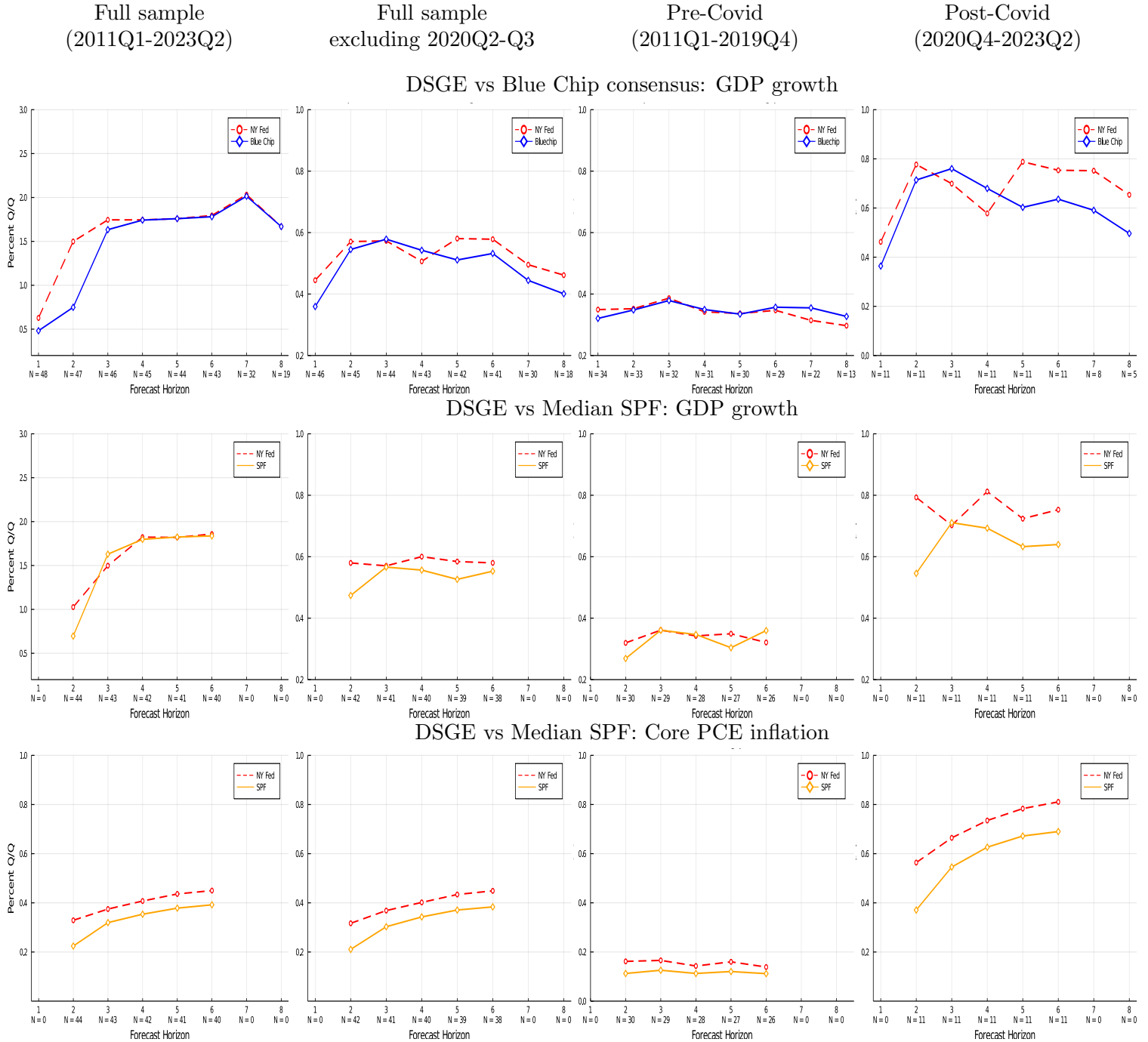
how we addressed these challenges in real time, and the DSGE’s few successes and many failures in forecasting the economy. From these failures we learn how the model can be improved.

2 The NY Fed’s DSGE Forecasting Performance

Many papers have documented the *pseudo* real-time out-of-sample forecasting performance of DSGE models (eg, Del Negro and Schorfheide, 2013, and the literature cited therein). While this literature uses real-time data to estimate the DSGE model(s) and produce the forecasts, the results still suffer of hindsight bias: the model (and the priors on the parameters) may be chosen knowing the results of the exercise. Here we document the *real* real-time out-of-sample performance of a DSGE model: the NY Fed model’s forecasts used to compute the root mean square errors (RMSEs) were produced for the FOMC policy cycle eight times a year starting in 2011, incorporated in FOMC memos or other internal documents, and made public since 2014 on the NY Fed’s [Liberty Street Economics](#) (LSE) blog.² The forecasting comparison setup is the same as in Cai et al. (2019), and for brevity we refer to this paper for details. One feature of the comparison is worth stressing here: the vintage of DSGE model forecast used to compare with professional forecasters is always earlier than the corresponding BCEI or SPF vintage, implying that the latter has an informational advantage relative to the DSGE (table A-1 in the appendix lists all the vintages used to compute the RMSEs). In the case of SPF this information advantage almost always amounts to having one more quarter of data (SPFs are collected right after the new BEA data are released, while DSGE forecasts are produced about two to three weeks before the previous FOMC meeting).

²FOMC memos are available at federalreserve.gov/monetarypolicy/fomc-memos.htm

Figure 1: Out-of-sample RMSEs



The left column of Figure 1 shows the RMSEs for the entire sample considered here, 2011Q1 to 2023Q2. We show results for quarterly GDP growth (BCEI vs DSGE in the first row and SPF vs DSGE in the second row) and quarterly core PCE inflation (SPF vs DSGE,

third row; BCEI do not forecast core PCE inflation). Especially for GDP growth the full sample results are of limited interest as they include the two quarters when growth swung dramatically because of the pandemic (2020Q2-Q3) and where the informational advantages had enormous consequences (eg, BCEI forecasts made in early April 2020 are compared to DSGE projections made in late January 2020). The second column shows the RMSEs excluding these two quarters and the next two columns decompose them into pre- (2011Q1-2019Q4) and post-Covid (2020Q4-2023Q2) RMSEs.

The results are as follows. First, the economy has become much harder to forecast after Covid: RMSEs for both output growth and inflation, and for both the DSGE and private forecasters, are at least twice as large in the post-2020Q4 period than in the pre-Covid one, except for very short horizons. This finding is not all that surprising for inflation, but is perhaps less known for output growth. Second, for output growth the DSGE forecasting accuracy is about as good as that of the *average* of private forecasters, especially for the pre Covid period. Recall that we are comparing the predictions of a single model—the DSGE—to those of forecast combinations. It is well known that such combinations are generally more accurate than their individual components. For the post-Covid period the DSGE is less accurate than private forecasters for long horizons, although this deterioration in accuracy is partly driven by forecasts made during the pandemic quarters (see appendix Figure [A-1](#)), which we discuss below. For core PCE inflation the DSGE is slightly less accurate than the average SPF before Covid—although some of this gap may be attributable to the informational advantage of the SPF which may matter more for inflation, which is more persistent than output growth. After Covid the gap between SPF and DSGE grows much larger.

Figure [A-2](#) provides the forecast errors two and six quarters ahead. It shows that espe-

cially six quarters ahead the DSGE and professional forecasters' forecasts are often similar, with two notable exceptions. One is the period after Covid, which we discuss next. The other is the first half of the 2010s, where the DSGE has consistently more pessimistic output projections compared to the SPF or BCEI. This pessimism, which was often correct, was driven by headwinds in the aftermath of the Great Recession (see Cocci et al., 2014). It translated into inflation forecasts that were below the 2 percent inflation target, and lower than the SPF projections. *Ex post*, these forecasts turned out to be too low.

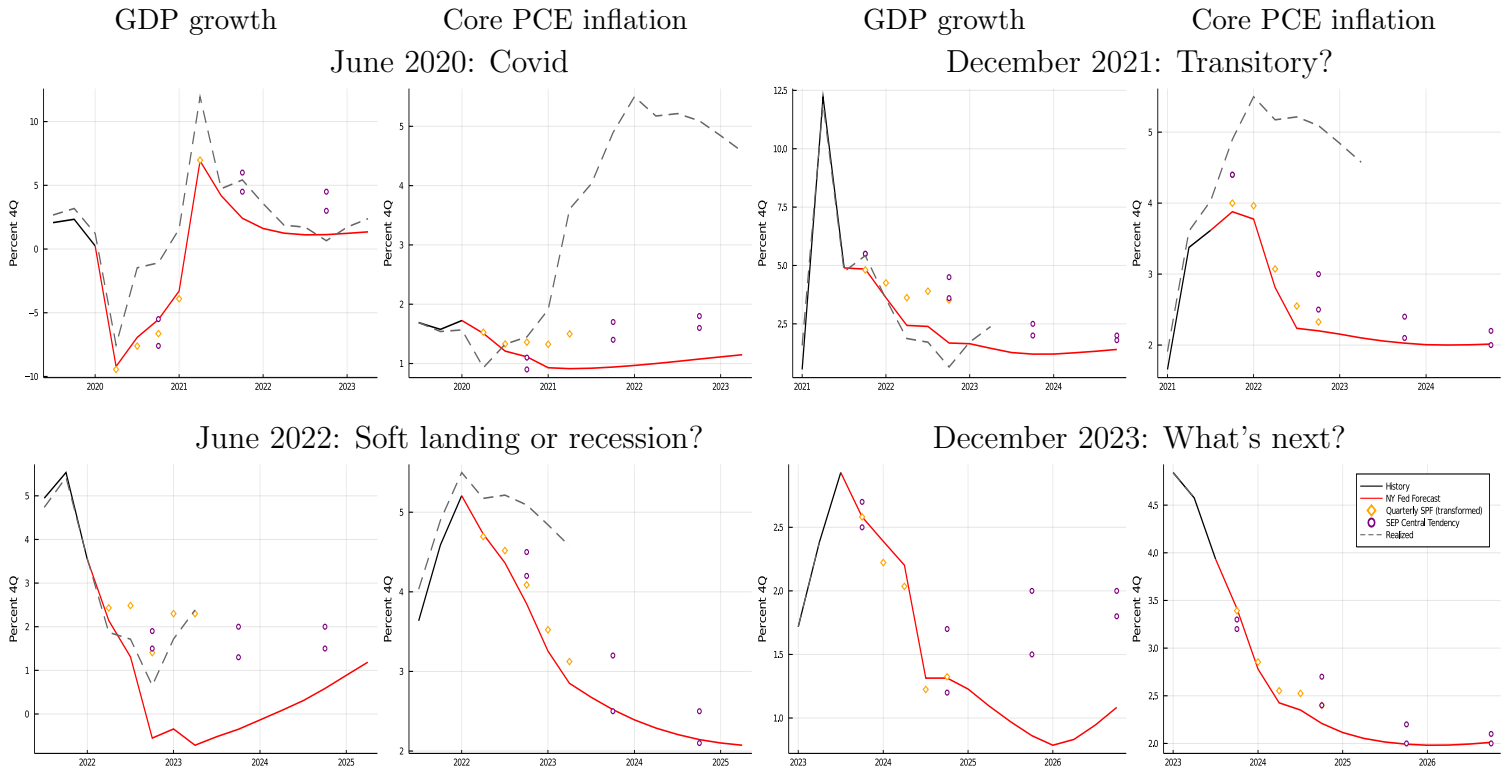
3 Covid and its aftermath—the NY Fed DSGE's take

This section revisits the recent history of the US economy through the lenses of the DSGE, focusing on four points in time. For each we discuss the model's interpretation of current events, and the rationale for its output growth and core PCE inflation forecasts, shown in Figure 2. We compare these forecasts, which were all published in LSE posts, to those of the SPF and the central tendency of the FOMC's Summary of Economic Projections (SEP).³

In the spring of 2020 we changed the model to accommodate the fact that the economic effects of Covid were different from those implied by standard recessions. We introduced a new set of temporary shocks (discount rate, productivity, and leisure preference shocks) whose importance (standard deviation) reflected our *a priori* uncertainty on whether the Covid shock reflected demand or supply factors. To incorporate the substantial uncertainty

³Figure A-3 shows the uncertainty around these projections, as well as forecasts of the natural rate of interest r^* and the FFR in real terms. In this section we show the SPF forecasts released before the corresponding FOMC cycle, as they were based on roughly the same information as the DSGE projections. Note that for computing the RMSEs in Figure 1 we use instead the SPF projections a quarter later.

Figure 2: Four episodes



Note: Solid red: NY Fed DSGE forecast; solid black: historical data available at the time; dashed black: revised data; yellow diamonds: SPF projections; purple circles: SEP central tendency.

surrounding the persistence of the effects of the pandemic we constructed three scenarios, which differed on the extent to which standard business cycle shocks were allowed to explain the effects of the pandemic as measured by the May SPF nowcasts for GDP growth and inflation in 2020Q2.⁴ The resulting mean GDP growth projections (red line) were roughly in line with SPF forecasts (yellow diamonds) for the first few quarters, and less optimistic than the SEP forecasts (purple circles) afterwards.⁵ The comparison with actual outcomes (dashed line) shows that the DSGE underestimated the speed of the recovery in 2020 and early 2021. Both SPF and SEP expected inflation to be well below 2 percent .in the aftermath of Covid, but the DSGE inflation forecasts even lower partly as a consequence of the weight

⁴See Figure A-4. The scenario weights were loosely informed by the SPF probability distribution.

⁵Only the nowcast was the same by construction since we treat the SPF nowcast as data when forecasting.

put on the more pessimistic scenarios.

The second point in time we consider is December 2021, after inflation had begun to rise dramatically.⁶ At the time, the SPF as well as the SEP expected strong growth in 2022, as they projected the level of economic activity to return to pre-Covid trends. The DSGE was more pessimistic, reflecting its view that the effects of the very expansionary monetary policy after Covid would wane over time, and turned out to be more correct. Its forecast of inflation, while not much different from the SPF one, was once again widely off the mark, however.⁷ What was the reason for the miss in forecasting inflation, other than the additional shock due to the Ukraine war? The DSGE attributed almost all of the surge in inflation up to then to cost-push shocks (see Del Negro et al., 2022),⁸ whose impact on inflation was expected to decline in line with the historical experience.⁹ One possibility is that post-Covid cost-push shocks had more persistent effects than the historical average. Another is that this representative agent model failed to recognize the impact of redistributive fiscal policy.

⁶Reflecting the new FOMC monetary policy strategy since 2020Q4 we replaced the historical (estimated) policy reaction function with a flexible average inflation targeting (AIT) reaction function. Its parameters were chosen so that the rule could rationalize the September 2020 pledge to keep rates at the ZLB for an extended period (early 2023, in line with expectations then) given projections for activity and inflation at that time. To prevent the model from front loading the effects of this policy change (Del Negro et al., 2023), we assumed that AIT was only gradually incorporated by the agents in forming expectations: these are formed using a convex combination of forecasts obtained under the old and the new policy reaction functions (see Chen et al., 2020, and the appendix for details).

⁷Unlike the SPF and DSGE, the SEP projections were informed by the December CPI report.

⁸Historically, cost-push shocks are responsible for about 20 percent of the variance of core PCE inflation.

⁹Accommodative monetary policy exacerbated the inflationary effects of cost-push shocks according to the model: when the FFR is at the ZLB, which we implemented as an occasionally binding constraint as in Cagliarini and Kulish (2013), inflationary cost-push shocks imply a real rate decline that stimulates demand.

By June 2022 the removal of policy accommodation had started in earnest. In order to inform the model about the expected pace of this removal we have been using FFR expectations from the Survey of Primary Dealers as a model observable. The DSGE did not believe in a “soft landing” and turned out to be wrong: the model predicted a drop in economic activity that never materialized. Inflation projections were in line with those of the SPF, and within the SEP central tendency, but were once again too optimistic.

The model sees the economy’s resilience over the past year-and-half as the result of productivity shocks, but mostly financial shocks: financial conditions, as measured in the model by corporate spreads, turned out stronger than predicted given the monetary tightening. Importantly for assessing the stance of monetary policy, such strength translates into a higher r^* , implying that policy may not be as restrictive as the FFR level would suggest. Growth is projected to decline to below trend during 2024, in line with the SPF, and to remain subdued in 2025 as the expansionary effect of strong financial conditions wanes. Inflation is forecast to decline toward 2 percent over time, as the effect of past cost-push shocks wanes and stronger productivity counteracts the demand side inflation induced by financial shocks.

4 Conclusions

Even if forecasting itself is not a model’s purpose, assessing its forecast accuracy is arguably one of the most stringent tests of its realism. If a model forecasts poorly, it is far from obvious why its quantitative results should be trusted, whether the model is used for policy counterfactuals or to understand economic developments. On this ground the NY Fed DSGE arguably gets a passing grade: its real time performance since 2011 has been on par with that of professional forecasters for output and a little worse for inflation. It has deteriorated

since Covid, partly as a result of taking the wrong side on many recent key issues, from how transitory the inflation bout was to whether disinflation was compatible with a soft landing. The DSGE's not so great performance for inflation suggests that more work is needed on this front. Alternative approaches that allow for heterogeneity should also be explored, and we have already started work along these lines at the NY Fed (Acharya et al., 2023).

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Online Appendix

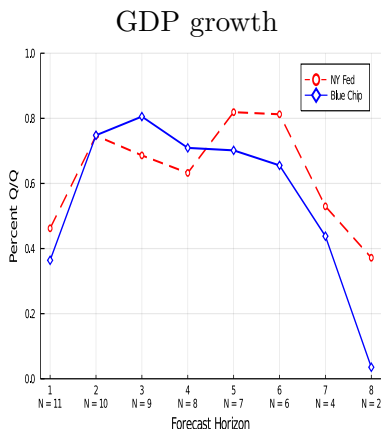
Table A-1: Vintages for Real Real-Time Forecast Comparison
(Vintages are in two digits for year-month-day)

Year- Quarter	Bluechip		SPF	
	Vintage	NYFed Vintage	Vintage	NYFed Vintage
2011-Q1	110410	110315		
2011-Q2	110710	110615	110513	110311
2011-Q3				
2011-Q4			111114	111019
2012-Q1	120410	120409	120210	120111
2012-Q2	120710	120605	120511	120409
2012-Q3	121010	120829		
2012-Q4	130110	121113		
2013-Q1	130410	130308	130215	130124
2013-Q2	130710	130613		
2013-Q3	131010	130912	130816	130723
2013-Q4	140110	131212	131125	131023
2014-Q1	140410	140313		
2014-Q2	140710	140610	140516	140423
2014-Q3	141010	140908	140815	140722
2014-Q4	150110	141209	141117	141021
2015-Q1	150410	150309	150213	150121
2015-Q2	150710	150610	150515	150421
2015-Q3	151010	150828	150814	150721
2015-Q4	160110	151204	151113	151014
2016-Q1	160410	160226	160212	160117
2016-Q2	160710	160527	160513	160418
2016-Q3	161010	160829	160812	160715
2016-Q4	170110	161129	161114	161021
2017-Q1	170410	170228	170210	170125
2017-Q2	170710	170606	170512	170411
2017-Q3	171010	170830	170811	170717

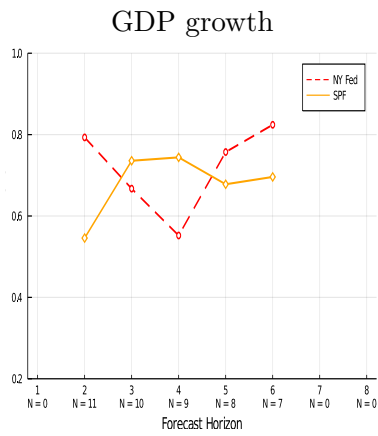
2017-Q4	180110	171204	171113	171017
2018-Q1	180410	180302	180209	180130
2018-Q2	180710	180629	180511	180302
2018-Q3	181010	180830	180810	180629
2018-Q4	190110	181130	181113	180830
2019-Q1	190410	190305	190322	181130
2019-Q2	190710	190531	190510	190418
2019-Q3	191010	190829	190809	190712
2019-Q4	200110	191118	191115	191017
2020-Q1	200410	200228	200214	200115
2020-Q2	200710	200604	200515	200410
2020-Q3	201010	200901	200814	200604
2020-Q4	210110	201117	201116	200901
2021-Q1	210410	210225	210212	210107
2021-Q2	210710	210601	210514	210412
2021-Q3	211010	210831	210813	210715
2021-Q4	220110	211129	211115	211019
2022-Q1	220410	220225	220211	220110
2022-Q2	220710	220705	220513	220225
2022-Q3	221010	220826	220812	220705
2022-Q4	230110	221116	221114	221014
2023-Q1	230410	230227	230210	230117
2023-Q2	230710	230606	230512	230419
2023-Q3	231010	230830	230811	230710

Figure A-1: Post-Covid (2020Q4-2023Q2) out-of-sample RMSEs using post-2020Q3 forecast vintages

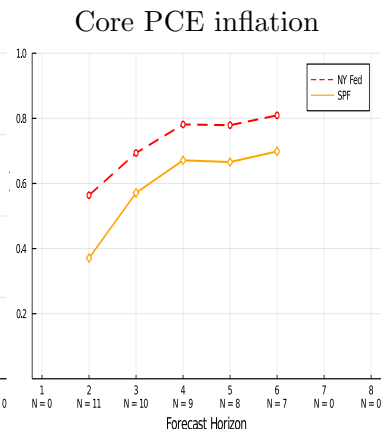
DSGE vs Blue Chip consensus:



DSGE vs Median SPF:

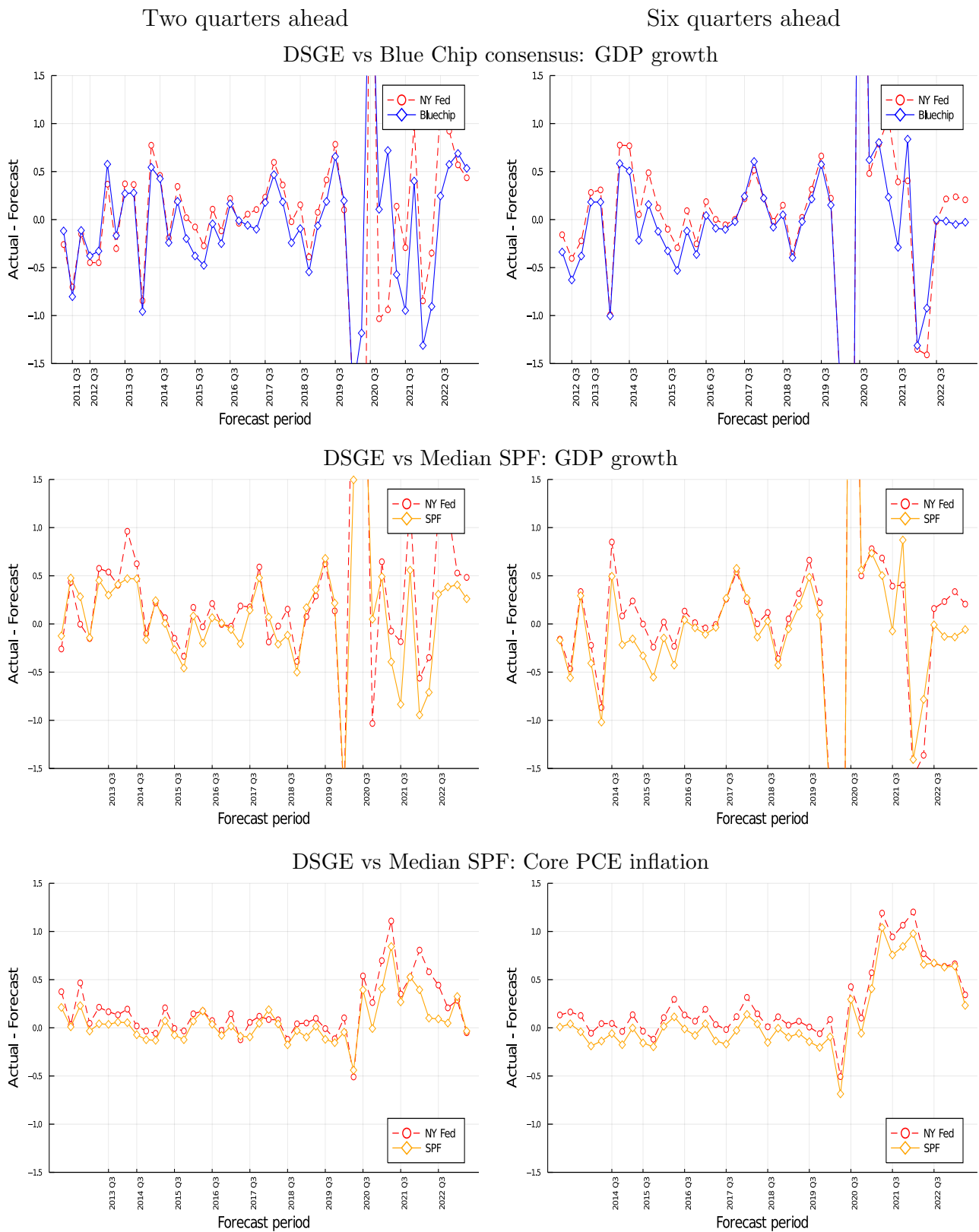


DSGE vs Median SPF:



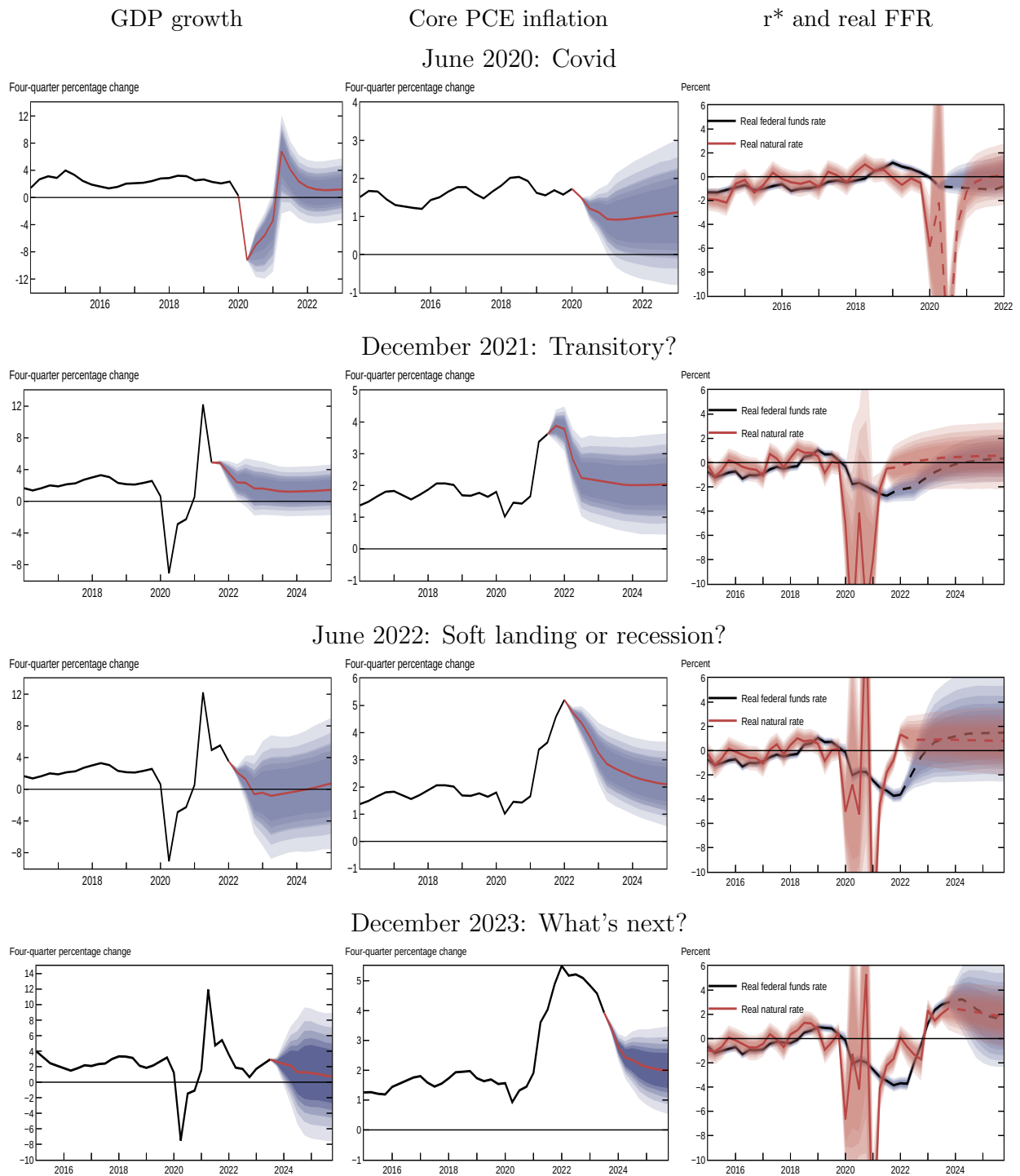
Note:

Figure A-2: Forecast errors: Actual - Forecasts



Note:

Figure A-3: Four episodes—additional figures



Note:

Figure A-4: Modeling the pandemic-scenarios

