Unconventional monetary policies and expectations on economic variables

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Abstract
We investigate whether forward guidance and large scale asset purchases are effective in steering economic expectations in the USA. Using the series of monetary policy shocks recovered in Swanson (J Monet Econ 118:32–53, 2021), local projections, and an algorithm to select the best empirical model, we show that unconventional monetary policies are effective in tilting economic expectations in a direction consistent with central bankers’ will. Our empirical findings provide two more insights: responses to LSAP shocks are stronger than those following a FG shock; responses to contractionary LSAP shocks are larger as compared to those stemming from expansionary ones.

Keywords Unconventional monetary policy · Local projections · Nonlinearities

JEL Classification E52 · E44 · E58

1 Introduction

In response to the great financial crisis first and the Covid-19 pandemic recently, and after interest rates hit the zero lower bound (ZLB), central banks around the world heavily relied on unconventional monetary policies (UMP). Forward guidance (FG) and large scale asset purchases (LSAP) are by now well-established tools.1

As for LSAP, various channels have been proposed that explain why asset purchases work. Among those theories, it has been argued that LSAP decrease the term premium

1 With FG we mean the communication by the Federal Open Market Committee (FOMC) about the likely future path of the federal funds rate over the next several quarters, whereas with LSAP the purchases by the Federal Reserve of longer-term U.S. Treasury bonds and mortgage-backed securities. The goal of both policies was to stimulate the economy by lowering longer-term U.S. interest rates.
component of longer maturities bonds (portfolio-balance effect); they enhance market functioning thanks to the presence of a large buyer playing the role of market maker and liquidity provider in a period of significant market distress; they provide a boost to risky asset prices prompting a positive wealth effect; and they can provide a signal to the markets, whereby asset purchases increase the probability that the policy interest rate will remain at its effective lower bound for a long time.

The extensive use of FG and LSAP boosted academic studies on their effectiveness which reached the conclusion that, indeed, both were effective in sustaining economic activity and prices during the recovery. This conclusion has been reached mainly looking at the impact of these measures on interest rates (see among others Gagnon et al. (2011), Krishnamurthy et al. (2011) and Swanson (2021)), economic activity and inflation (Weale and Wieladek 2016, Wu and Xia 2016).

UMP measures, however, are effective only to the extent that they consistently steer expectations towards the policy maker’s will. In this respect, Campbell et al. (2012) and Nakamura and Steinsson (2018) estimate the effects of monetary policy shocks on macroeconomic forecasts from the Blue Chip Economic Indicators survey, although neglecting LSAP from their analysis. Importantly, Nakamura and Steinsson (2018) find that forecasts on output growth increase following a contractionary monetary policy shock, suggesting the existence of a “Fed information effect” whereby private agents update their beliefs on the future state of the economy after observing Fed’s actions. For example, there could be times where individuals suddenly attach higher probabilities on the economy being in a better shape several quarters in the future after observing a higher-than-expected change in the Fed Funds rate. This causes their GDP forecasts to increase rather than decrease as standard theory would predict. Jarociński and Karadi (2020) and Miranda Agrippino and Ricco (2020) build econometric models that empirically disentangle standard monetary policy shocks from those stemming from the Fed’s outlook on economic activity. However, Bauer and Swanson (2020) question the existence of the information effect altogether by providing convincing evidence that what previous papers interpreted as a response to Fed’s private information really was a response to (omitted) economic information being revealed only after the monetary policy shock. Once one accounts for this, little or no Fed’s information effect is found in the data. In our paper, we do not find evidence for a Fed information effect either.

We use expectations on the left-hand side of a dynamic model, thereby implicitly assuming the possibility of a departure from full information rational expectations (FIRE) models. While our empirical models are silent on which part of the FIRE hypothesis fails (rationality of expectations, full information, or both) our impulse responses are consistent with a failure of that assumption and with some degree of information rigidity as documented in Coibion and Gorodnichenko (2015) and Coibion and Gorodnichenko (2012). Apart from the economic motive that warrants assessing the response of expectations to monetary policy shocks, there are two further and more technical reasons why using them might be beneficial. First, expectations tend to be much smoother (i.e. less noisy) than realized variables. Second, they undoubtedly respond to relevant economic news, although sometimes with lags. Those features can

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2 Greenlaw et al. (2018), where they argue that the impact of UMP are at best short lived, is a notable exception.
lead to a much higher signal-to-noise ratio in estimating IRFs than the case where one were to compute them on fuzzy realized variables.³

To the best of our knowledge, there is no empirical evidence in the literature showing in a unified framework the dynamic effects of FG and LSAP on economic agent’s expectations. As for the latter, there is no such evidence at all. The contribution of this paper is twofold: First, we fill this gap directly studying the impact of UMP on a broad range of professional macroeconomic expectations surveyed by Consensus Economics; second, we show that taking non-linearities into account is important to correctly assess the magnitude of the UMP impact.

To reach our goal, we use local projection methods and an optimizing routine that selects the empirical model that gives the best mix of fit and simplicity. Our approach is the simplest we could think of to save degrees of freedom and accommodate for the nonlinearity rising from asymmetry at the same time.

Operationally, we use the Federal Funds Rate (FFR), FG and LSAP shocks recovered in Swanson (2021) as forcing variables, together with some controls, in equations where expectations are on the left-hand side.⁴

It is important to disentangle the effects of UMP on expectations because this is arguably one of the main channels through which they affect economic activity. As structural forces pointed to an increased probability of reaching the ZLB in the future already before Covid-19 hit (Kiley and Roberts 2017) UMP currently are and will be again one of the main tools central banks will rely upon. Moreover, if UMPs are ineffective, then the ZLB constraint is more costly, and policymakers should try to avoid hitting it in the first place, for example by choosing a higher inflation target, as advocated, among others, by Summers (1991), Blanchard et al. (2010) and Ball (2014). On the other hand, if unconventional monetary policies do work, then the ZLB constraint may not be very costly implying there would be little reason for policymakers to raise their inflation target, at least on that ground.

Our main findings can be summarized as follows. First, using the linear model we show that both policies are able to steer economic expectations in the right direction. Second, LSAP is the most effective instrument as its impact on expectations is consistently stronger than other policies. Third, LSAP is more powerful when we isolate contractionary shocks: economic expectations react in a slightly stronger way and more significantly after a contractionary shock as opposed to an expansionary one.

Unfortunately, it is not easy to compare our results with previous studies as we focus on the impact on expectations as opposed to actual variables. However, somehow reassuringly, our responses for both expected GDP growth and inflation are inside the confidence interval found in Weale and Wieladek (2016) in their baseline monthly VAR estimates for actual GDP and inflation. An LSAP announcement of 1 percent of GDP leads to a statistically significant GDP peak response of roughly 0.3%; our estimates suggest that following a two standard deviations LSAP expansionary shock, GDP peak response is roughly equal to 0.2%. Moreover, the results on the asymmetry

³ This point has also been raised in Nakamura and Steinsson (2018). In their case though they implicitly assume FIRE.

⁴ We use state of the art identification procedure of FG and LSAP shocks because our primary aim is to study their impact on expectations. Of course we are not immune from any criticism on that identification procedure.
of LSAP is in line with what found by Angrist et al. (2018) and Tenreyro and Thwaites (2016) for conventional monetary policy.

In our view, our results can be used to shed some light on debates regarding the conduct of monetary policy. On the one hand, some members argue that acting pre-emptively with conventional monetary policy is the right thing to do because avoiding hitting the ZLB (or at least reducing the probability of hitting it) is of first-order importance; others say that ammunitions must be preserved for bad times when economic slowdown is clearly turning into recessions. Our results show that UMPs are effective and can be used as a tool in the conduct of monetary policy. However, the capability of LSAP in boosting economic activity and inflation might be overestimated by previous studies that do not take asymmetries into account so that the central bank should, in principle, try to avoid a situation where the only tool left to stimulate the economy are UMPs. Therefore, we believe our results lend some support to monetary policy acting in a pre-emptive manner. The paper is organized as follows: the next session describes the data and the estimation procedure. Section 3 discuss the results in both the linear and nonlinear model. Section 4 provides some robustness check. Section 5 concludes presenting also some policy implications.

2 Data and estimation

We borrow unconventional monetary policy shocks from Swanson (2021), who estimates them by joining the high frequency identification approach together with further structural schemes. In particular, Swanson computes the high-frequency (30-minute) response of asset prices to FOMC announcements to identify the immediate causal effect of those announcements on financial markets. He then tests for the number of dimensions underlying those announcement effects and shows that they are well described by three dimensions. These represent the three aspects of FOMC announcements that had the greatest systematic effect on asset prices over the sample; intuitively, the three dimensions are likely to correspond to changes in the federal funds rate, changes in forward guidance, and changes in LSAPs.

The three factors are estimated as the first principal components of those asset price responses. To provide structural interpretation of the factors, Swanson searches over all possible rotations of the three principal components to find one in which the first factor corresponds to the change in the federal funds rate, the second one to the change in forward guidance, and the third to the change in LSAPs. Rotations are recovered conditional on three identifying assumptions: (i) changes in LSAP have no effect on the current federal funds rate, (ii) changes in FG have no effects on the current federal funds rate, (iii) LSAP had no significant role before the ZLB period. Swanson (2021) shows how both FG as well as LSAP factors have been buffeted both by positive and negative shocks. In the model, we assign day-specific high-frequency shocks to their corresponding months, an approach that is similar in spirit to what done in Angrist et al. (2018) within their context of policy rate change prediction with future contracts.

We rely on Consensus Economics to retrieve expectations on various variables. Consensus provides a monthly survey where it asks professional forecasters to assess what their outlook is regarding economic and financial variables (for a very wide set
of countries), and we are interested in one-year-ahead forecasts for some selected US variables. The issue with the survey is that the horizon is not fixed, i.e., forecasters provide predictions for the full current and following calendar year, meaning that forecasts made in (e.g.) October have a great deal more information than those made in (e.g.) March. In order to obtain fixed-horizon forecasts, we take weighted averages of forecasts for the current and following calendar year, where weights are set so as to maintain a constant one-year forecast horizon\(^5\). We use expectations on GDP growth, inflation in the Consumer Price Index, and the Unemployment Rate.

We estimate a monthly linear model using the data described previously. We first discuss the estimation strategy and the details about our model selection approach, which will be used also in Sect. 4 for the state-dependent case. Then, we turn to the actual results for the linear case.

2.1 A model for the transmission of shocks to expectations

As for DGP choice, we deliberately choose to impose as few assumptions as we can by using an optimizing routine which selects models that fit well the data without growing too large in parameters. In this respect, the local projections framework proves particularly suited to perform this exercise on a very large set of plausible models. The linear model we want to estimate is

\[
y_{t+s} = \alpha_s + \left[ \sum_{p=0}^{L} \theta_p FFR_{t-p} + \gamma_p FG_{t-p} + \psi_p LSAP_{t-p} \right] \\
+ \sum_{p=1}^{L} \beta_p X_{t-p} + u_{t+s} \quad s = 0, 1, 2, \ldots, H, \tag{1}
\]

where \( y \) is some mapping of the variable whose dynamic response we want to track, FFR, FG and LSAP are Federal Funds Rate, Forward Guidance and LSAP shocks, respectively, and \( X_t \) is a vector of control variables. While in this paper we are interested in UMPs, we nevertheless include conventional monetary policy shocks into the analysis so to exploit all relevant information and provide the reader with a full picture of the effects of monetary policy onto expectations. Estimation is performed separately for each horizon and for each dependent variable with OLS over the period July 1991 until February 2020. Generally speaking, the IRFs we are interested in are defined by the sequence \( \{ \gamma_s^0, \psi_s^0 \}_{s=0}^H \), where inference is performed with Newey-West standard errors. While in the regression for the unemployment rate we plug expectations in level, for variables expressed as expected growth rates IRFs are cumulated in the following way:

\[
g_t^{m} = (1 + g_t^y)^{\frac{1}{12}} - 1, \tag{2}
\]

\[
y_{t+s} = 100 \prod_{h=0}^{s} (1 + g_{t+h}^{m}), \tag{3}
\]

\(^5\) This approach has first been proposed in Brooks et al. (2004).
where $g^m_t$ is the monthly-wise one-year-ahead expected growth rate of a given variable, and the forecast is produced with information available up to time $t$.

Usually, researchers tend to discretionally decide the set of variables $X_t$ to be included as well as the number of lags, whereas a minority of papers selects the number of lags with information criteria. In our work, we aim at estimating both the variables to be included in the model and the number of lags at each horizon. In particular, we estimate with OLS all the combinations of variables and lags subject to the constraint that the number of lags in each candidate model have to be the same across variables, and that there cannot be “holes” in the actual lag structure, namely that whenever the $p$-th lag appears in the equation, the same has to be true also for the $(p-1)$-th, $(p-2)$-th, ... , first lag. We then select the model that gives the best score as gauged by the AICu developed in McQuarrie et al. (1997). In this way we are able to reduce the total number of combinations from an order of $10^{18}$ to a few thousands models at every horizon. Moreover, not only the constraints on the lag structure greatly reduce the computational burden, but they also yield much more stable parameters estimates. Section 3.3 shows that, in our application, using this procedure allows to extract a greater amount of signal from the series, generally yielding larger estimates than if we had chosen the model in a discretionary way.

Since we have exogenous shocks at our disposal, the only reason we use this approach is because we want to obtain the most efficient estimates we possibly can, and we do this by selecting the regressors that maximize the most some penalized likelihood function. When we fit our model with UMP shocks only (a theoretically valid alternative) we obtain IRFs that are broadly similar to ours, although less precise.

As we said, the recent literature on monetary policy has departed from the purely linear VAR to focus instead on possible state-contingencies in the transmission of monetary policy to the rest of the economy, and here we follow the same route. In particular, we are interested in whether expansionary monetary shocks have had a different effect on expectations than contractionary ones. To this end, we want to estimate a slightly more involved version of equation (1):

$$ y_{t+s} = \alpha_s + \left[ \sum_{p=0}^{L} \text{FFR}_{t-p} \left( \theta^p_s + \mathbb{1}_{\text{FFR}_{t-p}>0} - \mathbb{1}_{\text{FFR}_{t-p}<0} \right) + \right. $$

$$ + \text{FG}_{t-p} \left( \gamma^p_s + \mathbb{1}_{\text{FG}_{t-p}>0} - \mathbb{1}_{\text{FG}_{t-p}<0} \right) + $$

$$ + \text{LSAP}_{t-p} \left( \psi^p_s + \mathbb{1}_{\text{LSAP}_{t-p}>0} - \mathbb{1}_{\text{LSAP}_{t-p}<0} \right) \left. \right] + \sum_{p=1}^{L} \beta^p X_{t-p} + u_{t+s} \quad s = 0, 1, 2, \ldots, H, $$

where $\theta^p_s$ ($\theta^p_s$) is a state-dependent parameter which represents the effect of an expansionary (contractionary) Federal Funds Rate shock. The same interpretation is

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6 FFR, FG and LSAP shocks are always included in the model, but their lag is selected just as the other (common to all variables) ones.
given to $\gamma \cdot (\psi \cdot \cdot)$ as what regards FG (LSAP) shocks. $X_t$ is a matrix of potential controls, which include the autoregressive component, the one-, two-, and ten-years yield on US bonds, the Moody’s Seasoned Baa Corporate bond yield in excess of the ten-year yield on US bonds, actual values for industrial production growth, inflation, and the unemployment rate.\(^7\)

Finally, note that the local projection method allows us to run partially-state-dependent regressions, whereby we assume state-contingent parameters only on the monetary shocks, but we leave the rest of the model to be a linear one. Given well-known degrees of freedom problems with macro data, this is a very useful possibility that we exploit in order to limit the proliferation of parameters.

### 2.2 Model-selection results for the linear case

Before discussing impulse responses, we would like to digress a little about results related to our model selection approach which we believe are worthwhile to highlight. Table 1 shows actual model selection at each horizon when the dependent variable is expected GDP growth. Different models have obviously been estimated for different dependent variables, but some general patterns turn out to be quite common for all of them, so we focus on expected GDP growth as a representative variable for the purposes of our discussion.

As one could expect, the auto-regressive component is always included. Moreover, the average number of selected lags is equal to 1.8. This is a sensible result, the reason being that autocorrelated expectations terms are among the predictors, and if those expectations have been formed taking into account much of the available information at the time of the survey, the first lag should already be capable of providing a large share of the overall predictive power. Furthermore, while model selection tends to choose very few lags, it instead finds that many covariates help predict the dependent variable at hand. Once more, this result is sensible and could be explained by the fact that while expectations are very persistent and extremely smooth in their behavior, the latest changes in the broad economy tend to cause agents to somehow revise their view of how the world will evolve.

### 3 Econometric results

Table 2 reports estimated peak responses for both the linear and the nonlinear model when a one-standard-deviation shock to FFR, FG or LSAP occurs. In the linear model, variables are responding to an expansionary shock. While in this paper we are interested in the effect of UMPs, we still show results related to FFR shocks. In particular, the linear specification provides no evidence of a Fed’s information effect, something that is consistent with what recently found in Bauer and Swanson (2020).

\(^7\) In the working paper version of this paper, we used a shorter sample and were able to use the excess bond premium from Gilchrist and Zakrajšek (2012) instead of the corporate spread above. While in no way we are claiming the two series represent the same phenomenon, they are highly correlated.
Table 1 Model selection for expected GDP

| Horizon | Lags | Var #1      | Var #2      | Var #3      | Var #4      | Var #5      | Var #6      |
|---------|------|-------------|-------------|-------------|-------------|-------------|-------------|
| 0       | 3    | Exp GDP     | 1Y yield    | IP growth   | Baa spread  |             |             |
| 1       | 3    | Exp GDP     | 2Y yield    | IP growth   | Inflation   | Baa spread  |             |
| 2       | 2    | Exp GDP     | 1Y yield    | 2Y yield    | IP growth   | Inflation   | Baa spread  |
| 3       | 2    | Exp GDP     | 1Y yield    | 2Y yield    | IP growth   | Inflation   | Baa spread  |
| 4       | 2    | Exp GDP     | 1Y yield    | 2Y yield    | IP growth   | Inflation   | Baa spread  |
| 5       | 2    | Exp GDP     | 1Y yield    | 2Y yield    | IP growth   | Inflation   | Baa spread  |
| 6       | 2    | Exp GDP     | 1Y yield    | 2Y yield    | IP growth   | Inflation   | Baa spread  |
| 7       | 2    | Exp GDP     | 1Y yield    | 10Y yield   | IP growth   | Inflation   | Baa spread  |
| 8       | 2    | Exp GDP     | 1Y yield    | 10Y yield   | IP growth   | Inflation   | Baa spread  |
| 9       | 2    | Exp GDP     | 1Y yield    | 10Y yield   | IP growth   | Inflation   | Baa spread  |
| 10      | 2    | Exp GDP     | 1Y yield    | 10Y yield   | IP growth   | Inflation   | Baa spread  |
| 11      | 2    | Exp GDP     | 1Y yield    | 10Y yield   | IP growth   | Inflation   | Baa spread  |
| 12      | 2    | Exp GDP     | 1Y yield    | 10Y yield   | IP growth   | Inflation   | Baa spread  |
| 13      | 2    | Exp GDP     | 1Y yield    | 10Y yield   | IP growth   | Inflation   | Baa spread  |
| 14      | 2    | Exp GDP     | 1Y yield    | 10Y yield   | IP growth   | Inflation   | Baa spread  |
| 15      | 2    | Exp GDP     | 1Y yield    | 10Y yield   | IP growth   | Inflation   | Baa spread  |
| 16      | 2    | Exp GDP     | 1Y yield    | 2Y yield    | IP growth   | Inflation   | Baa spread  |
| 17      | 1    | Exp GDP     | 1Y yield    | 2Y yield    | Inflation   |             |             |
| 18      | 1    | Exp GDP     | 1Y yield    | 2Y yield    | Inflation   |             |             |
| 19      | 1    | Exp GDP     | 1Y yield    | 2Y yield    | Inflation   |             |             |
| 20      | 1    | Exp GDP     | 1Y yield    | 2Y yield    | Inflation   |             |             |
| 21      | 1    | Exp GDP     | 1Y yield    | 2Y yield    | Inflation   |             |             |
| 22      | 1    | Exp GDP     | 1Y yield    | 2Y yield    | Inflation   |             |             |
| 23      | 1    | Exp GDP     | 1Y yield    | 2Y yield    | Inflation   |             |             |
| 24      | 1    | Exp GDP     | 1Y yield    | 2Y yield    | Inflation   |             |             |

The table shows selected models at each horizon when the dependent variable is expected GDP growth and the model is the linear one. The maximum number of lags is set to be equal to 4, and the information criterion we used is the AICu.

In general, one can see that expectations respond in a much stronger way to LSAP shocks than they do to FG ones. Peaks in the linear model show that LSAP shocks cause expectations to be revised more than twice as much as they do under FG shocks. Moreover, both UMPs feature relatively delayed responses. Linear estimates mask substantial heterogeneity in responses depending on whether the underlying shock is a contractionary or an expansionary one. Section 3.2 discusses those results in greater detail.

3.1 Results: the linear case

Figure 1 shows linear responses in expectations following a one-standard-deviation shock. As for Forward Guidance, broadly speaking, coefficients have the expected
Table 2  Peak responses

|            | GDP     | Inflation | Unempl. rate |
|------------|---------|-----------|--------------|
| FFR        | −0.02 (10) | 0.02 (9)  | −0.06 (24)   |
| FFR Exp.   | −0.05 (16) | 0.04 (24) | −0.06 (24)   |
| FFR Contr. | −0.15 (19) | 0.04 (8)  | 0.24 (19)    |
| FG         | 0.05 (16)  | 0.02 (22) | −0.02 (16)   |
| FG Exp.    | 0.07 (15)  | 0.13 (24) | 0.11 (24)    |
| FG Contr.  | −0.06 (24) | 0.08 (24) | 0.08 (24)    |
| LSAP       | 0.11 (16)  | 0.07 (24) | −0.14 (23)   |
| LSAP Exp.  | 0.09 (12)  | 0.06 (11) | −0.07 (4)    |
| LSAP Contr.| −0.19 (22) | −0.27 (24)| 0.27 (20)    |

The first row reports peak values of the impulse response functions in the linear model for expectations of economic variables following a one standard deviation shock in the federal funds rate (corresponding months are in parenthesis). The second and third rows report results when the model is split to take into account expansionary and contractionary shocks in the federal funds rate. The subsequent rows refer to Forward Guidance and LSAP.

**Fig. 1**  Linear IRFs. The figure plots IRFs of our dependent variables after a one standard deviation expansionary shock of each of FFR, FG, and LSAP. Bands are 68% confidence intervals.
sign, although responses are significant for expected GDP growth only. As anticipated, responses from LSAP shocks are much larger as well as more precisely estimated, suggesting that Forward Guidance is likely a less effective tool at least as what concerns the impact on expectations.

Recall that each IRFs is estimated horizon-by-horizon and that our algorithm selects potentially different models at each step. Interestingly, even if selected models are indeed changing at every horizon, parameters estimates are surprisingly robust as judged by the smooth behavior of IRFs. There exist only one case where parameters abruptly change after sixteen months, namely GDP growth following an FG shock.

3.2 Results: the nonlinear case

In this section, we show that in some cases IRFs estimated in the linear model hide an important source of heterogeneity, namely the one stemming from the sign of the shock. Again, although they are not our primary focus, we still show estimates stemming from FFR shocks. Conventional monetary policy seems to have a counter-intuitive effect only as what concerns the behavior of expected GDP growth following a contractionary FFR shock. The remaining responses either confirm the non-existence of a Fed’s information effect, or they show standard signs. More interestingly, the strength of all responses stemming from exogenous LSAP variation mainly comes from contractionary shocks, whereas expansionary ones yield smaller although significant responses.

Figure 2 plots IRFs for expected GDP. One can see that expansionary Forward Guidance has a somehow short-lived impact on expectations. Indeed, expected GDP reaches a barely significant peak after 14 months, but it then becomes insignificantly different from zero at longer horizons. Contractionary FG does seem to have some significant effect on expected economic activity, whereby GDP is revised down the most after two years. IRFs after LSAP behave differently: expansionary shocks have a much stronger as well as more persistent effect than they do under FG.

As for prices, Fig. 3 shows that expansionary FG and LSAP are able to raise expectations in a quite significant manner, with the first leading to much higher responses than the latter. However, while in this case contractionary shocks to FG show a puzzling behavior in expected CPI inflation, contractionary LSAP does lower expected prices by as much as a 0.27 pp after two years.

Expectations on the unemployment rate (Fig. 4) again show much clearer responses when they are hit by an LSAP shock than by FG ones. In particular, contractionary FG shocks prove to have somewhat ambivalent effects, although in the longer term they do worsen the outlook for unemployment. Instead, LSAP shocks consistently cause expectations to be revised in the standard way, and crucially they do so in a clearly stronger manner when they are contractionary.

3.3 Discretionary model selection

We now show results obtained from a model where we use the whole set of controls and four lags for each variable, without performing any model selection. In this way
we are able to discern whether our selection procedures significantly improves over a discretionary approach.

Figure 5 shows IRFs from the linear model estimated with the two methods. First, among the IRFs that are estimated to be significant at some horizon, the majority of those that are estimated with our procedure are stronger than those obtained with a discretionary model; this is especially true for IRFs obtained from an LSAP shock. This is important because, if we were to only look at results from the discretionary model, we would conclude that LSAPs affect expectations in a much milder way than we would think otherwise, thereby changing our understanding of the expectations channel of monetary policy. Second, even though our approach yields at times different estimates, it tends to do so while yielding point estimates that fall within the confidence bands from the discretionary model. This is reassuring because, if the shock was not exogenous, we could have observed potentially very different (biased) IRFs depending on the exact specification.

All in all, we conclude that our automatic model selection is able to extract a higher amount of signal from the series and, as a consequence, it depicts a clearer picture
Fig. 3 Cumulative IRFs, Inflation. The figure plots cumulated one-year-ahead expected CPI response together with 68% confidence intervals of the quantitative assessment of the effects of monetary shocks on economic agents’ expectations.

4 Robustness check

As we showed, our estimation strategy enormously restricts the degrees of freedom available to us by letting the data choose the best model to be fit at every horizon, selecting both variables and lags. Therefore, we have much less concern about convincing the reader that the model is robust to a different lag and/or variable choice, the reason being indeed that we are not choosing them to begin with.

Nevertheless, we ran some robustness to check whether using different information criteria yields similar results than those obtained with the AICu. We performed estimates from models that have been selected using the AIC (Akaike 1973), the AICc (Hurvich and Tsai 1989), and the BIC. The AICc was introduced after acknowledging that the AIC tended to select models which overfitted the data in small samples. Therefore, the AICc adds to the AIC an additional non-stochastic term of order $T^{-1}$, which is meant to further penalize regressors in finite samples, whereas it asymptotically converges to the AIC.
Both the AIC and the AICc use a maximum likelihood estimator for the standard error of the regression, meaning that no adjustment for degrees of freedom is applied when dividing the residual sum of squares by the number of observations. McQuarrie et al. (1997) therefore build the AICu criterion (our preferred information criterion) which is identical to the AICc apart from the presence of the adjustment for the degrees of freedom, further showing that the AICu is an approximate unbiased estimator of the Kullback–Leibler information. This information criterion is able to outperform others (including the AICc) for a wide range of data generating processes and sample sizes. Only when the true model is among the candidate ones does the BIC perform better than the AICu, and this is a natural result given that the BIC indeed is a consistent selection method under the aforementioned condition.

Having said this, Table 3 shows selected models for each horizon when the information criterion is the BIC. As compared to Table 1, it is apparent that this criterion is more parsimonious. Indeed, the average number of selected predictors (except for the shocks which are always included in the model) equals 6.0 with the BIC, whereas it equals 9.6 with the AICu. For the other methods (namely the AIC and the AICc)

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8 The average is taken over the H+1 horizons.
Fig. 5  Automatic versus discretionary model selection. The figure plots IRFs estimated from discretionary selection of the model (blue distribution) and the point-estimate IRFs from the corresponding model selected with our automatic procedure (black line), following a one standard deviation shock

...this number is even higher. Notably however, results are robust to using all those very different criteria.9

5 Concluding remarks and policy implications

In this paper, we estimate the causal effect of unconventional monetary policy interventions onto expectations on future economic activity and other relevant macroeconomic variables. We find that Large-Scale Asset Purchases have been very effective in steering expectations in the right direction, while Forward Guidance yields more subdued and not always clear responses.10

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9 Related figures are available to the reader upon request.

10 As the Riksbank tirelessly repeats “the interest rate path is a forecast, not a promise”. Woodford (2013) comments on the Riksbank’s approach to monetary policy and state “there is no suggestion that the exercise is anything but a purely forward-looking consideration, repeated afresh in each decision cycle, of which of the feasible forward paths for the economy from that date onward is most desirable, […] . Indeed, it stresses that the appropriate repo-rate path will be reassessed in each decision cycle”.

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Moreover, digging deeper into the possible existence of non-linearities in the transmission mechanism, we find that not taking asymmetry explicitly into account may lead to an overestimation of the impact of LSAP on the economy.

Our evidence suggests that policies like LSAP which deliver concrete actions bring with themselves a stronger (credibility) effect than others where policymakers report their own (potentially imprecise) forecast of what they think they are most likely to do in the future (like FG).11

On the methodological side, we are the first (to the best of our knowledge) to exploit the flexibility of local projections and account for model uncertainty by jointly estimating both the set of variables and the number of lags at each horizon. By imposing

11 In September 2018 median FOMC members’ projections about end-of-2019 target rate was 3.0%; at the end of November 2019 the target range was already 1.5–1.75%.
certain restrictions on the universe of models to search for, we are able to reduce the
total number of candidate models from an order of $10^{18}$ to just a few thousands.
Interestingly, notwithstanding the fact that we use different conditioning variables,
IRF estimates prove to be surprisingly stable throughout the horizon with very few exceptions.

Our results show that UMPs have been effective in sustaining economic activ-
ity through their impact on expectations. We are therefore confident that they could
be deployed successfully to counter the impact of future recessions, with a caveat:
because of the fact that asymmetry has not been taken into account, some of the esti-
mated expansionary capability of LSAPs detected by past literature might have been
overestimated. At the same time, the contractionary effects of monetary tightenings
could be stronger.

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