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UNCONVENTIONAL MONETARY POLICIES AND EXPECTATIONS ON ECONOMIC VARIABLES

by Alessio Anzuini* and Luca Rossi*

Abstract

We investigate whether forward guidance and large scale asset purchases are effective in steering economic expectations in the US. Using the series of monetary policy shocks recovered in Swanson (2020), 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 both types of policies are larger after contractionary shocks as compared to expansionary ones.

JEL Classification: E52, E44, E58.
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Contents

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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 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.[2] 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 (2020)), 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

* We would like to thank Eric Swanson for sharing his monetary policy shocks. We also thank participants at the 14^{th} South-Eastern European Economic Research Workshop at the Bank of Albania for useful comments. The views expressed in this paper are those of the authors and do not necessarily reflect those of the Bank of Italy. All the remaining errors are ours.

[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.

[2] Greenlaw et al. (2018), where they argue that the impact of UMP are at best short lived, is a notable exception.

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 between the monetary policy shock and the first available forecast. 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.

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 immediately respond to relevant economic news. Those features can 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

[3]This point has also been raised in Nakamura and Steinsson (2018).

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 non-linearity rising from asymmetry at the same time.

Operationally, we use FG and LSAP shocks recovered in Swanson (2020) 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, UMPs are more powerful when we isolate contrac-

[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.

tionary 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 one standard deviation LSAP expansionary shock, GDP peak response is roughly equal to 0.2%. Moreover, the results on the asymmetry of UMPs 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 UMP are effective and can be used as a tool in the conduct of monetary policy. However, their capability 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 UMP. 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 non-linear model. Section 4 provides some robustness check. Section 5 concludes presenting also some policy implications.

2 Data and Estimation

We borrow the monthly unconventional monetary policy shocks from Swanson (2020), which 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 over the period from 1991 to 2019. 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. In Figure 1 we reproduce a chart from the original work of Swanson (2020), where it appears clear that the FG and LSAP factors recovered have been buffeted by both positive and negative shocks.

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), 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, Personal Consumption growth, Business Investment growth, Industrial Production 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 Section 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

$$y_{t+s} = \alpha_s + \left[\sum_{p=0}^{L} \gamma_s^p \mathrm{FG}_{t-p} + \psi_s^p \mathrm{LSAP}_{t-p} \right] + \sum_{p=1}^{L} \boldsymbol{\beta}_s^p \mathbf{X}_{t-p} + u_{t+s} \quad s = 0, 1, 2, \dots, H, \tag{1}$$

where $\mathbf{y}$ is some mapping of the variable whose dynamic response we want to track, **FG** and **LSAP** are Forward Guidance and LSAP shocks respectively, and $\mathbf{X}_t$ is a vector of control variables. Estimation is performed *separately* for each horizon and for each dependent variable with OLS. 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

[5] This approach has first been proposed in Brooks et al. (2004).

variables expressed as expected growth rates IRFs are cumulated in the following way:

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

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

where g_t^m 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 $\mathbf{X}_t$ 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 principle, one could estimate a least absolute shrinkage and selection operator (LASSO) model[6], which under certain conditions asymptotically selects exactly the variables (and lags) that are relevant. Following Belloni and Chernozhukov (2013), one could perform OLS post-estimation using only the consistently estimated set of relevant variables. This step would be necessary because, even where the LASSO would consistently select the true set of relevant covariates, its estimates would have (by construction) a strong bias.

Therefore, one could estimate an adaptive LASSO model[7], which (as opposed to the standard LASSO) by its very construction enjoys the oracle property, meaning that the algorithm consistently selects the right set of variables. We first tried this approach, but we disappointingly obtained similar results as those found in Mullainathan and Spiess (2017) for the standard LASSO, whereby parameters estimates turned out to be quite unstable, even after re-estimating the model with OLS on the selected covariates. The reason why this is the case might be that the number of observations for the oracle property to reasonably kick in might be deceptively high and unlikely to be reached with the short samples tipically available in macro data.

[6] See Tibshirani (1996).
[7] See Zou (2006).

We therefore turned to a more computationally-intensive but more promising approach, at least for the econometric problem we have to deal with. 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[8]. We then select the model that gives the best score as gauged by standard information criteria. 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, yielding more precise and somehow larger estimates than if we had chosen the model in a discretionary way.

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):

$$\begin{aligned} y_{t+s} = & \alpha_s + \left[\sum_{p=0}^{L} \mathrm{FG}_{t-p} \left(\gamma_s^{p,+} \mathbb{1}_{\mathrm{FG}_{t-p}>0} + \gamma_s^{p,-} \mathbb{1}_{\mathrm{FG}_{t-p}<0} \right) + \right. \\ & \left. + \mathrm{LSAP}_{t-p} \left(\psi_s^{p,+} \mathbb{1}_{\mathrm{LSAP}_{t-p}>0} + \psi_s^{p,-} \mathbb{1}_{\mathrm{LSAP}_{t-p}<0} \right) \right] + \\ & + \sum_{p=1}^{L} \beta_s^p \mathbf{X}_{t-p} + u_{t+s} \quad s = 0, 1, 2, \ldots, H, \end{aligned} \tag{4}$$

[8] FG and LSAP shocks are always included in the model, but their lag is selected just as the other (common to all variables) ones.

where $\gamma_{\cdot}^{\cdot,+}$ ($\gamma_{\cdot}^{\cdot,-}$) is a state-dependent parameter which represents the effect of an expansionary (contractionary) Forward Guidance shock. The same interpretation is given to $\psi_{\cdot}^{\cdot,\cdot}$ as what regards LSAP shocks. $\mathbf{X}_t$ is a matrix of potential controls, which include the autoregressive component, the one-, two-, and ten-years yield on US bonds, the excess bond premium from Gilchrist and Zakrajšek (2012), actual (not expected) values for industrial production growth, inflation, and the unemployment rate, and the two FG and LSAP state dummies.

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 number of selected lags is almost always equal to one apart from the first months where 2 lags are selected. This (i.e. the low number of selected lags) makes sense, the reason being that autocorrelated expectations terms are among the predictors, and if those expectations have been formed taking into account all the available information at the time of the survey, the first lag should be sufficient to capture also past evolutions of the actual underlying variable. 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.

Interestingly, the 10-year yield on Treasury bonds appears in the equations roughly after 2 years for all the variables we analyzed. This again makes sense because the predictive horizon of the other yields we use is indeed no longer than two years, meaning that variation below this horizon is better captured by the price of shorter term bonds.

3 Econometric Results

Table 2 reports estimated peak responses for both the linear and the non-linear model when a one-standard-deviation shock to either FG or LSAP occurs. In the linear model, variables are responding to an *expansionary* shock.

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 roughly twice as much as they do under FG shocks. Moreover, both UMPs feature very delayed responses, even though (apart from the unemployment rate) responses to LSAP tend to peak earlier than those occurring after FG policies are enacted. 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 2 shows linear responses in expectations following a FG shock. Broadly speaking, coefficients have the expected sign, and the significance of the responses is highest for GDP, consumption, and investment. Also, responses up to the first year are extremely subdued and mostly insignificantly different from zero both from a statistical but in some cases also from an economic perspective. Figure 3 shows linear responses after LSAP shocks. As anticipated, responses are much larger, relatively more front-loaded, and also more precisely estimated.

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 two cases where parameters abruptly change towards the end of the response horizon, namely investment and industrial production following an FG shock.

3.2 Results: the non-linear case

In this section, we show that IRFs estimated in the linear model hide an important source of heterogeneity, namely the one stemming from the sign of the shock. In particular, the strength of the majority of the responses mainly comes from contractionary shocks, whereas expansionary ones yield smaller, although significant, responses especially as what concerns FG shocks.

Figure 4 plots IRFs for expected GDP. One can see that expansionary Forward Guidance has a somehow short-lived impact on expectations. Indeed, expected GDP increases up to 0.17 percentage points (pp) within the first 18 months, but it then becomes insignificantly different from zero at longer horizons. Contractionary FG does instead have lasting effects on expected economic activity, whereby GDP is revised down a significant 0.3 pp after 4 years. IRFs after LSAP seem to behave slightly differently: expansionary shocks have a stronger and more persistent effect than they do under FG, whereas contractionary ones peak well before, and their effect vanishes by the end of the horizon.

As for prices, Figure 5 shows that expansionary FG and LSAP are able to raise expectations by 0.12 and 0.14 pp respectively, with the latter displaying much higher significance level. Contractionary FG does not curb expectations much throughout the whole time horizon, as opposed to contractionary LSAP which does lower expected prices by as much as a 0.2 pp after three years (at 90% significance level).

Expectations on the unemployment rate (Figure 6) are more affected by contractionary shocks on both UMPs than they are by expansionary ones: the effects of the former is at most half the latter. As for the other variables (Figures 7-9) similar considerations apply.

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.

Figures 10 and 11 show IRFs from the linear model estimated with the two methods. First, one can notice that not using our procedure leads to less significant IRFs. This is something one could have expected, since automatic selection looks for models that indeed have a lower penalized standard error of the regression, which in turn leads (ceteris paribus) to a lower standard error for the parameters. Second, responses estimated with our procedure are notably stronger than those obtained with a discretionary model, and 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 unconventional monetary policies affect expectations in a much milder way than we would think otherwise, thereby changing our understanding of the expectations channel of monetary policy. Third, even though our approach yields quite 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 significantly higher amount of signal from the series and, as a consequence, it depicts a much clearer picture 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 provide some robustness by showing that using different information criteria yields similar results than those obtained with the BIC. We present results from models that have been selected using the AIC (Akaike (1973)), the AICc (Hurvich and Tsai (1989)), and the AICu (McQuarrie et al. (1997)). 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 asymptotically it 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 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 other criteria (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 informaton criterion is the AICu. As compared to Table 1, it is apparent that this criterion is less parsimonious. Indeed, the average number of selected predictors[9] (except for the shocks which are always included in the model) equals 6.6 with the BIC, whereas it equals 10.4 with the AICu. For the other methods (namely the AIC and the AICc) this number is even higher. Notably however, results are robust to using all those very different criteria. Figures 12-17 show IRFs when the criterion is the AICu, whereas for brevity we avoided to plot IRFs for the other two criteria, which are available to the reader upon request.

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 (*on average*) both Forward Guidance and Large-Scale Asset Purchases have been effective in steering expectations in the right direction. Importantly however, LSAP shocks cause responses to be much greater, more front-loaded, and more precisely estimated than FG do.[10]

[9]The average is taken over the H+1 horizons.

[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*".

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 UMP on the economy.

Our evidence suggest 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 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 UMP have been effective in sustaining economic activity through their impact on expectations. We are therefore confident that they could be deployed successfully to counter the impact of future reecessions, with a caveat: because of the fact that asymmetry has not been taken into account, some of their estimated expansionary capability detected by past literature might have been overestimated. At the same time, the contractionary effects of monetary tightenings could be stronger.

[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%.

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Table 1: Model Selection for Expected GDP

Horizon	Lags	Var #1	Var #2	Var #3	Var #4	Var #5	Var #6	Var #7
0	2	Exp GDP	EBP GK	IP growth				
1	2	Exp GDP	EBP GK	IP growth	Inflation			
2	2	Exp GDP	EBP GK	IP growth	Inflation			
3	2	Exp GDP	1Y yield	2Y yield	EBP GK	IP growth	Inflation	
4	2	Exp GDP	1Y yield	2Y yield	EBP GK	Inflation		
5	1	Exp GDP	1Y yield	2Y yield	EBP GK	Inflation	Unempl.	
6	1	Exp GDP	1Y yield	2Y yield	EBP GK	IP growth	Inflation	
7	1	Exp GDP	1Y yield	2Y yield	EBP GK	IP growth	Inflation	
8	1	Exp GDP	1Y yield	2Y yield	EBP GK	IP growth	Inflation	
9	1	Exp GDP	1Y yield	2Y yield	EBP GK	IP growth	Inflation	
10	1	Exp GDP	1Y yield	2Y yield	EBP GK	IP growth	Inflation	
11	1	Exp GDP	1Y yield	2Y yield	EBP GK	IP growth	Inflation	
12	1	Exp GDP	1Y yield	2Y yield	EBP GK	IP growth	Inflation	
13	1	Exp GDP	1Y yield	2Y yield	EBP GK	IP growth	Inflation	
14	1	Exp GDP	1Y yield	2Y yield	EBP GK	IP growth	Inflation	Unempl.
15	1	Exp GDP	1Y yield	2Y yield	EBP GK	IP growth	Inflation	Unempl.
16	1	Exp GDP	1Y yield	2Y yield	EBP GK	IP growth	Inflation	Unempl.
17	1	Exp GDP	1Y yield	2Y yield	EBP GK	Inflation	Unempl.	
18	1	Exp GDP	1Y yield	2Y yield	EBP GK	Inflation	Unempl.	
19	1	Exp GDP	1Y yield	2Y yield	EBP GK	Inflation	Unempl.	
20	1	Exp GDP	1Y yield	2Y yield	EBP GK	Inflation	Unempl.	
21	1	Exp GDP	1Y yield	2Y yield	EBP GK	Inflation	Unempl.	
22	1	Exp GDP	1Y yield	2Y yield	EBP GK	Inflation	Unempl.	
23	1	Exp GDP	1Y yield	2Y yield	EBP GK	10Y yield	Inflation	Unempl.
24	1	Exp GDP	1Y yield	2Y yield	EBP GK	10Y yield	Inflation	Unempl.
25	1	Exp GDP	1Y yield	2Y yield	EBP GK	10Y yield	Inflation	Unempl.
26	1	Exp GDP	1Y yield	2Y yield	10Y yield	Inflation	Unempl.	
27	1	Exp GDP	1Y yield	2Y yield	10Y yield	Inflation	Unempl.	
28	1	Exp GDP	1Y yield	2Y yield	10Y yield	Inflation	Unempl.	
29	1	Exp GDP	1Y yield	2Y yield	10Y yield	Inflation	Unempl.	
30	1	Exp GDP	1Y yield	2Y yield	10Y yield	Inflation	Unempl.	
31	1	Exp GDP	1Y yield	2Y yield	10Y yield	Inflation	Unempl.	
32	1	Exp GDP	1Y yield	2Y yield	10Y yield	Inflation	Unempl.	
33	1	Exp GDP	1Y yield	2Y yield	10Y yield	Inflation	Unempl.	
34	1	Exp GDP	1Y yield	2Y yield	10Y yield	Inflation	Unempl.	
35	1	Exp GDP	1Y yield	2Y yield	10Y yield	IP growth	Inflation	Unempl.
36	1	Exp GDP	1Y yield	2Y yield	10Y yield	IP growth	Inflation	Unempl.
37	1	Exp GDP	1Y yield	2Y yield	10Y yield	IP growth	Inflation	Unempl.
38	1	Exp GDP	1Y yield	10Y yield	Inflation	Unempl.		
39	1	Exp GDP	1Y yield	10Y yield	IP growth	Inflation	Unempl.	
40	1	Exp GDP	1Y yield	10Y yield	10Y yield	IP growth	Inflation	Unempl.
41	1	Exp GDP	1Y yield	EBP GK	10Y yield	IP growth	Inflation	Unempl.
42	1	Exp GDP	1Y yield	EBP GK	10Y yield	IP growth	Inflation	Unempl.
43	1	Exp GDP	1Y yield	EBP GK	10Y yield	IP growth	Inflation	Unempl.
44	1	Exp GDP	1Y yield	EBP GK	10Y yield	IP growth	Inflation	Unempl.
45	1	Exp GDP	1Y yield	EBP GK	10Y yield	IP growth	Inflation	Unempl.
46	1	Exp GDP	1Y yield	EBP GK	10Y yield	IP growth	Inflation	Unempl.
47	1	Exp GDP	1Y yield	EBP GK	10Y yield	IP growth	Inflation	Unempl.
48	1	Exp GDP	1Y yield	EBP GK	10Y yield	IP growth	Inflation	Unempl.

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 BIC.

Table 2: Peak Responses

	FG	LSAP	FG Exp.	FG Cont.	LSAP Exp.	LSAP Cont.
GDP	0.11 (48)	0.18 (25)	0.09 (19)	-0.31 (48)	0.17 (40)	-0.40 (24)
Inflation	0.07 (48)	0.15 (46)	0.12 (33)	-0.05 (48)	0.14 (47)	-0.20 (36)
Unempl. rate	-0.07 (17)	-0.14 (26)	-0.06 (16)	0.14 (35)	-0.12 (38)	0.37 (28)
Industrial Prod.	0.11 (48)	0.34 (26)	0.13 (19)	-0.24 (46)	0.27 (41)	-0.70 (23)
Consumption	0.07 (48)	0.13 (32)	0.04 (17)	-0.23 (47)	0.11 (41)	-0.36 (23)
Investment	0.39 (45)	0.89 (27)	0.15 (16)	-1.09 (36)	0.69 (39)	-1.81 (27)

The first column reports peak values of the impulse response functions in the linear model for expectations of economic variables following a one standard deviation shock in forward guidance (corresponding months are in parenthesis). The second column reports peak results for large scale asset purchases in the same model. Columns from third to sixth report results when the model is split to take into account expansionary and contractionary shocks in both UMPs.

Table 3: Model Selection for Expected GDP

Horizon	Lags	Var #1	Var #2	Var #3	Var #4	Var #5	Var #6	Var #7	Var #8
0	2	Exp GDP	2y yield	EBP GK	IP growth	Inflation			
1	2	Exp GDP	1y yield	2y yield	EBP GK	IP growth	Inflation	Unempl.	
2	2	Exp GDP	1y yield	2y yield	EBP GK	IP growth	Inflation	Unempl.	
3	2	Exp GDP	1Y yield	2Y yield	EBP GK	IP growth	Inflation	Unempl.	
4	2	Exp GDP	1Y yield	2Y yield	EBP GK	IP growth	Inflation	Unempl.	
5	2	Exp GDP	1Y yield	2Y yield	EBP GK	IP growth	Inflation		
6	2	Exp GDP	1Y yield	2Y yield	EBP GK	IP growth	Inflation		
7	1	Exp GDP	1Y yield	2Y yield	EBP GK	IP growth	Inflation		
8	1	Exp GDP	1Y yield	2Y yield	EBP GK	IP growth	Inflation		
9	1	Exp GDP	1Y yield	2Y yield	EBP GK	IP growth	Inflation		
10	1	Exp GDP	1Y yield	2Y yield	EBP GK	IP growth	Inflation		
11	1	Exp GDP	1Y yield	2Y yield	EBP GK	IP growth	Inflation	Unempl.	
12	1	Exp GDP	1Y yield	2Y yield	EBP GK	IP growth	Inflation	Unempl.	
13	1	Exp GDP	1Y yield	2Y yield	EBP GK	IP growth	Inflation	Unempl.	
14	1	Exp GDP	1Y yield	2Y yield	EBP GK	IP growth	Inflation	Unempl.	
15	1	Exp GDP	1Y yield	2Y yield	EBP GK	IP growth	Inflation	Unempl.	
16	1	Exp GDP	1Y yield	2Y yield	EBP GK	IP growth	Inflation	Unempl.	
17	1	Exp GDP	1Y yield	2Y yield	EBP GK	10y yield	IP growth	Inflation	Unempl.
18	1	Exp GDP	1Y yield	2Y yield	EBP GK	10y yield	IP growth	Inflation	Unempl.
19	1	Exp GDP	1Y yield	2Y yield	EBP GK	10y yield	IP growth	Inflation	Unempl.
20	1	Exp GDP	1Y yield	2Y yield	EBP GK	10y yield	IP growth	Inflation	Unempl.
21	1	Exp GDP	1Y yield	2Y yield	EBP GK	10y yield	Inflation	Unempl.	
22	1	Exp GDP	1Y yield	2Y yield	EBP GK	10y yield	Inflation	Unempl.	
23	1	Exp GDP	1Y yield	2Y yield	EBP GK	10Y yield	Inflation	Unempl.	
24	1	Exp GDP	1Y yield	2Y yield	EBP GK	10Y yield	Inflation	Unempl.	
25	1	Exp GDP	1Y yield	2Y yield	EBP GK	10Y yield	Inflation	Unempl.	
26	1	Exp GDP	1Y yield	2Y yield	EBP GK	10y yield	Inflation	Unempl.	
27	1	Exp GDP	1Y yield	2Y yield	10Y yield	Inflation	Unempl.		
28	1	Exp GDP	1Y yield	2Y yield	10Y yield	Inflation	Unempl.		
29	1	Exp GDP	1Y yield	2Y yield	10Y yield	Inflation	Unempl.		
30	1	Exp GDP	1Y yield	2Y yield	10Y yield	Inflation	Unempl.		
31	1	Exp GDP	1Y yield	2Y yield	10Y yield	Inflation	Unempl.		
32	1	Exp GDP	1Y yield	2Y yield	10Y yield	IP growth	Inflation	Unempl.	
33	1	Exp GDP	1Y yield	2Y yield	10Y yield	IP growth	Inflation	Unempl.	
34	1	Exp GDP	1Y yield	2Y yield	10Y yield	IP growth	Inflation	Unempl.	
35	1	Exp GDP	1Y yield	2Y yield	10Y yield	IP growth	Inflation	Unempl.	
36	1	Exp GDP	1Y yield	2Y yield	10Y yield	IP growth	Inflation	Unempl.	
37	1	Exp GDP	1Y yield	2Y yield	10Y yield	IP growth	Inflation	Unempl.	
38	3	Exp GDP	1Y yield	10Y yield	Inflation	Unempl.			
39	3	Exp GDP	1Y yield	10Y yield	Inflation	Unempl.			
40	3	Exp GDP	1Y yield	10Y yield	Inflation	Unempl.			
41	3	Exp GDP	1Y yield	10y yield	Inflation	Unempl.			
42	3	Exp GDP	1Y yield	EBP GK	10Y yield	IP growth	Inflation	Unempl.	
43	3	Exp GDP	1Y yield	EBP GK	10Y yield	IP growth	Inflation	Unempl.	
44	3	Exp GDP	1Y yield	EBP GK	10Y yield	IP growth	Inflation	Unempl.	
45	3	Exp GDP	1Y yield	EBP GK	10Y yield	IP growth	Inflation	Unempl.	
46	3	Exp GDP	1Y yield	EBP GK	10Y yield	IP growth	Inflation	Unempl.	
47	3	Exp GDP	1Y yield	EBP GK	10Y yield	IP growth	Inflation	Unempl.	
48	3	Exp GDP	1Y yield	EBP GK	10Y yield	IP growth	Inflation	Unempl.	

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.

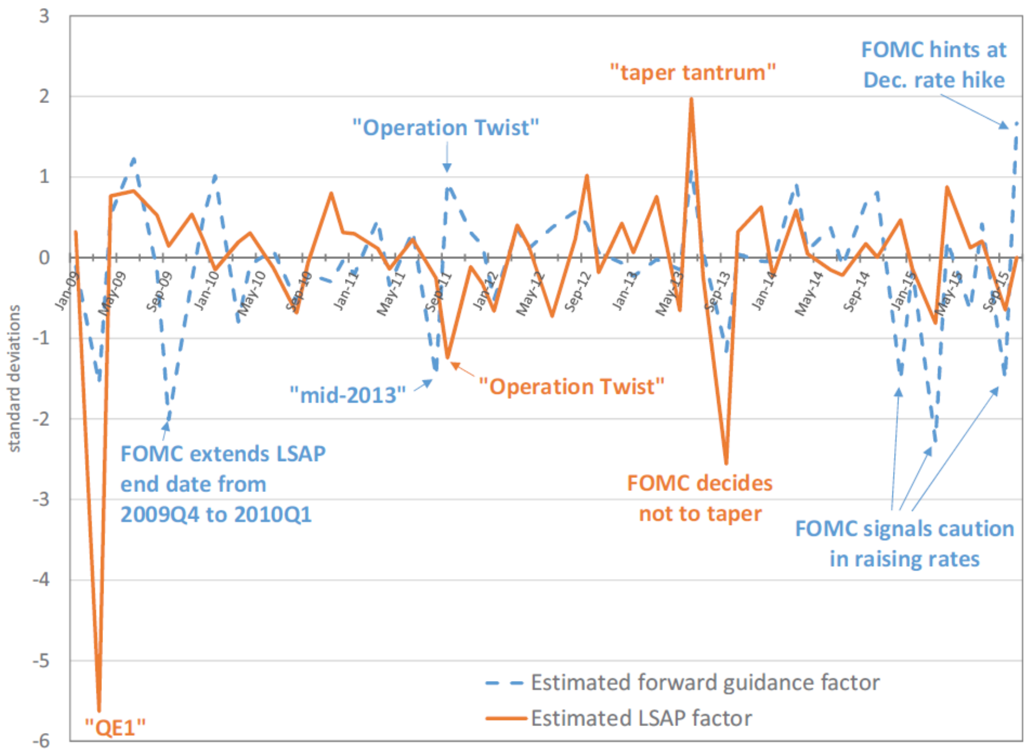

Figure 1: Swanson Estimated Factors. Plot of estimated forward guidance (dashed blue line) and LSAP (solid orange line) factors over time. Notable FOMC announcements are labelled in the figure for reference. The LSAP factor is multiplied by minus 1 in the figure so that positive values in the figure correspond to interest rate increases.

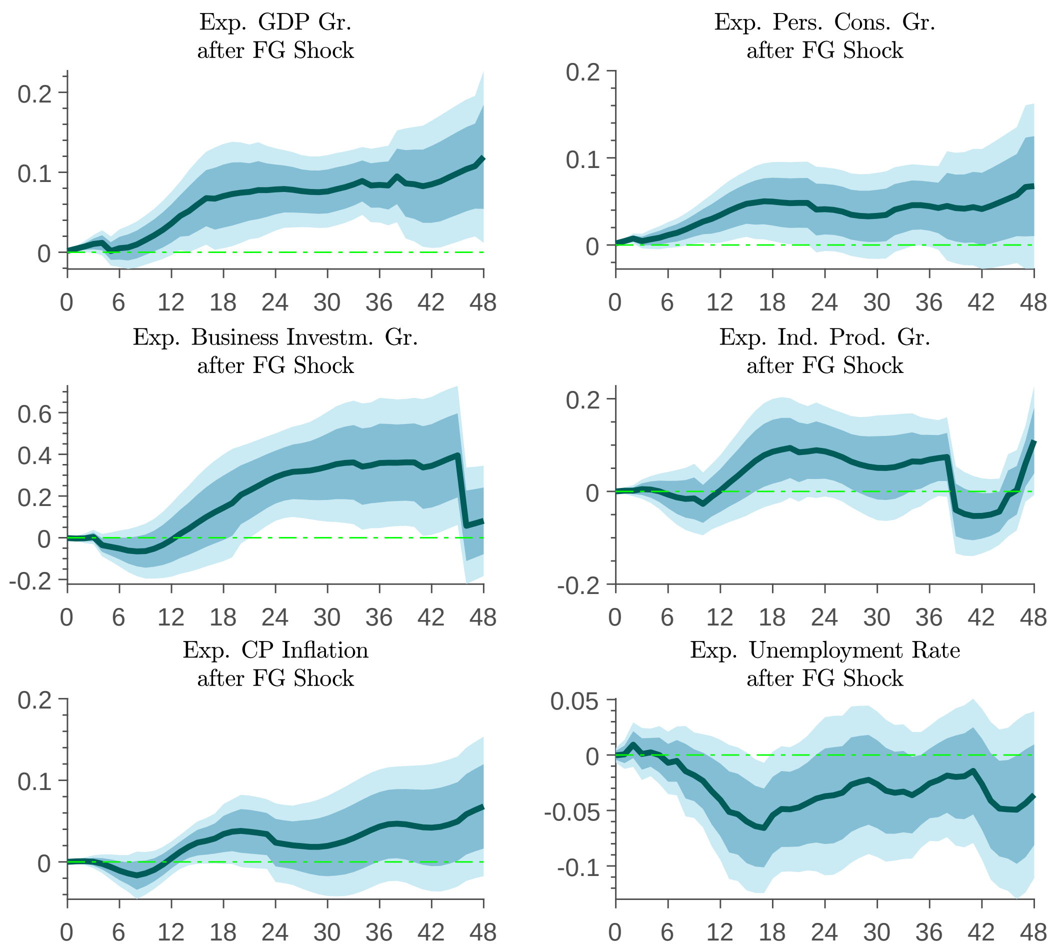

Figure 2: IRFs Forward Guidance. The figure plots cumulated one-year-ahead IRFs of expected variables, together with 68% and 90% confidence intervals, following a one standard deviation FG shock.

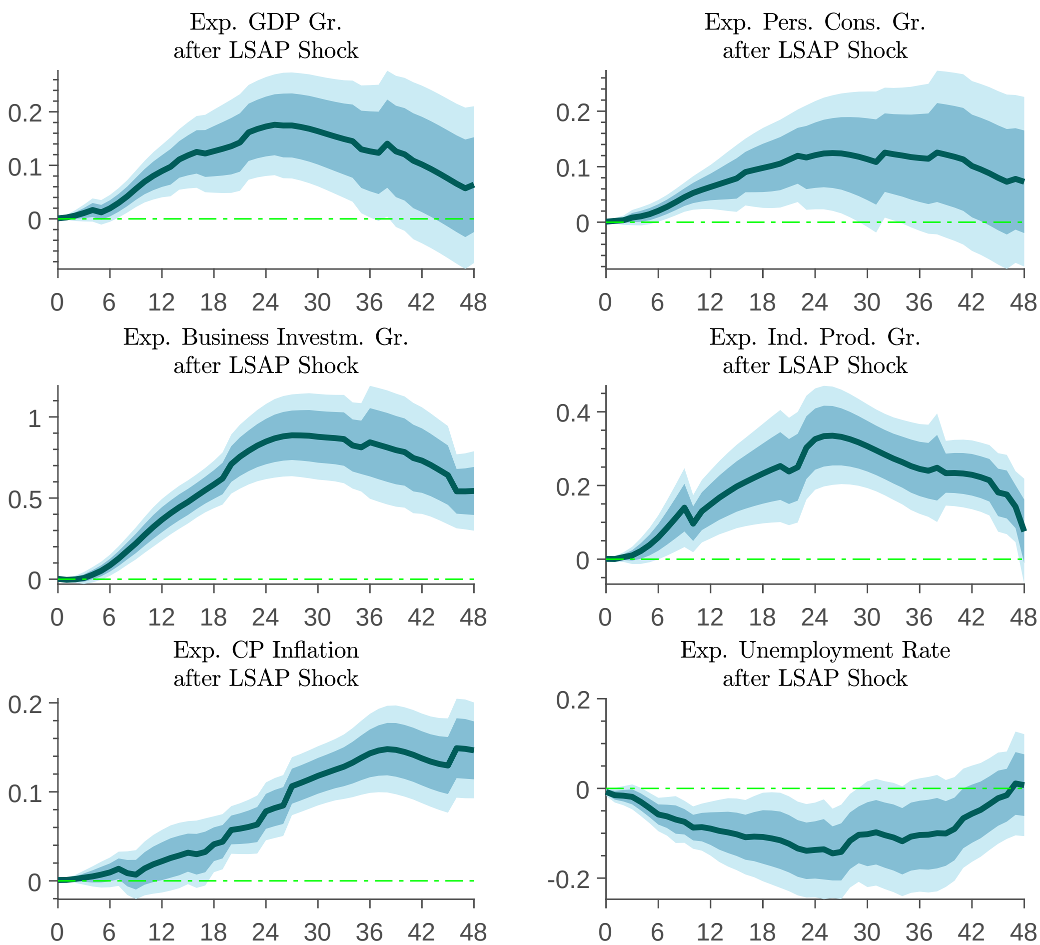

Figure 3: **IRFs Large Scale Asset Purchase.** The figure plots cumulated one-year-ahead IRFs of expected variables, together with 68% and 90% confidence intervals, following a one standard deviation LSAP shock.

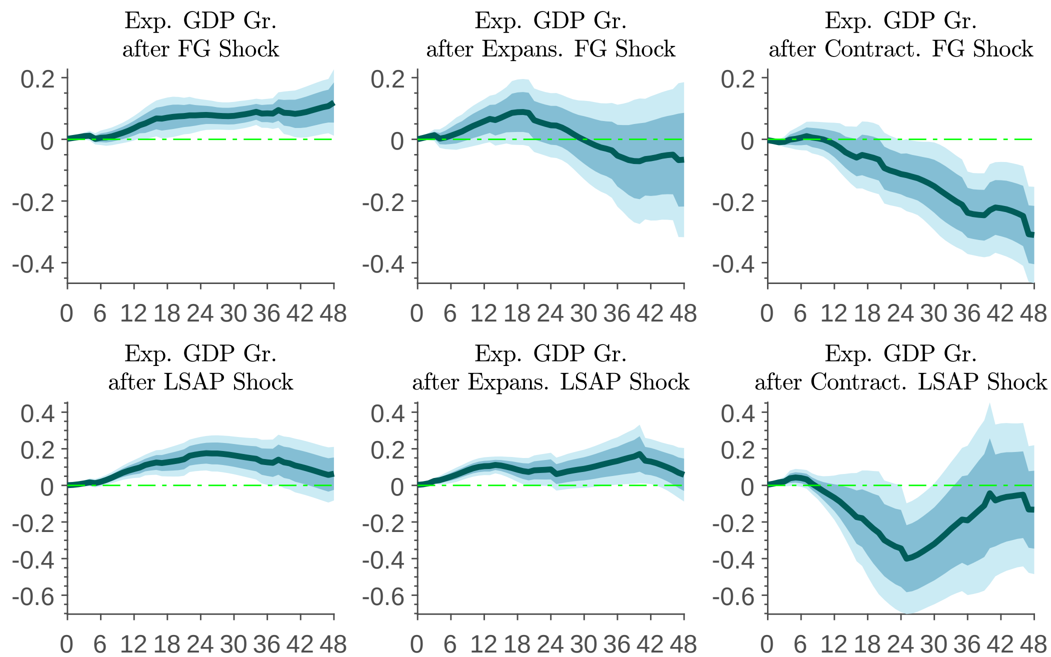

Figure 4: Cumulative IRFs, GDP. The figure plots one-year-ahead expected GDP response together with 68% and 90% confidence intervals. The first column displays the responses to an expansionary FG and LSAP shocks in the linear model. The second and the third columns the asymmetric responses to an expansionary and a contractionary FG and LSAP shocks.

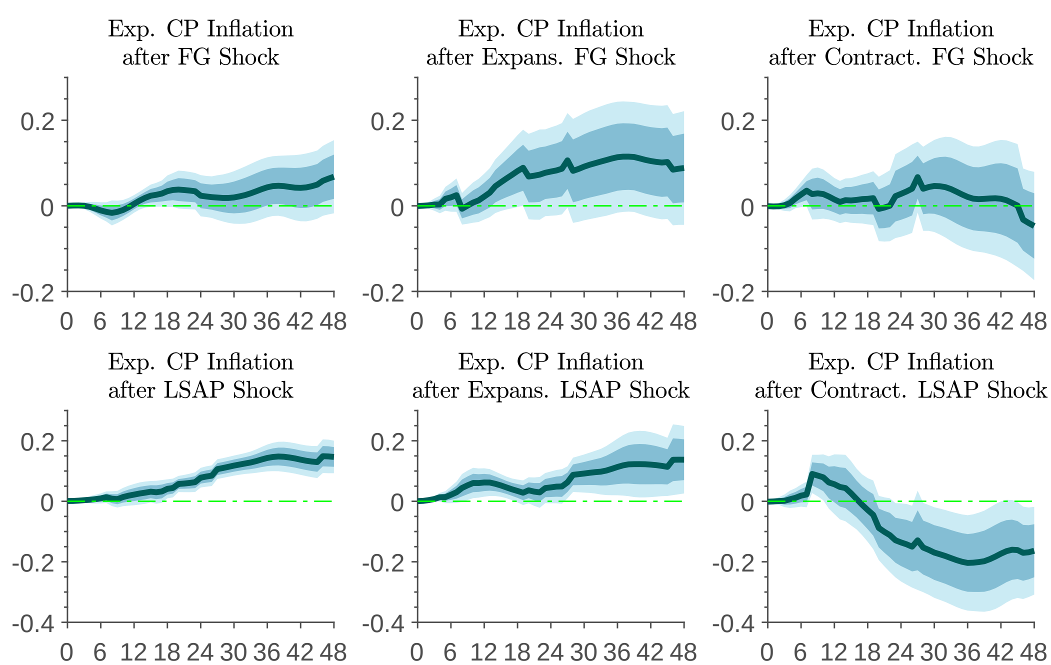

Figure 5: Cumulative IRFs, Inflation. The figure plots cumulated one-year-ahead expected CPI response together with 68% and 90% confidence intervals.

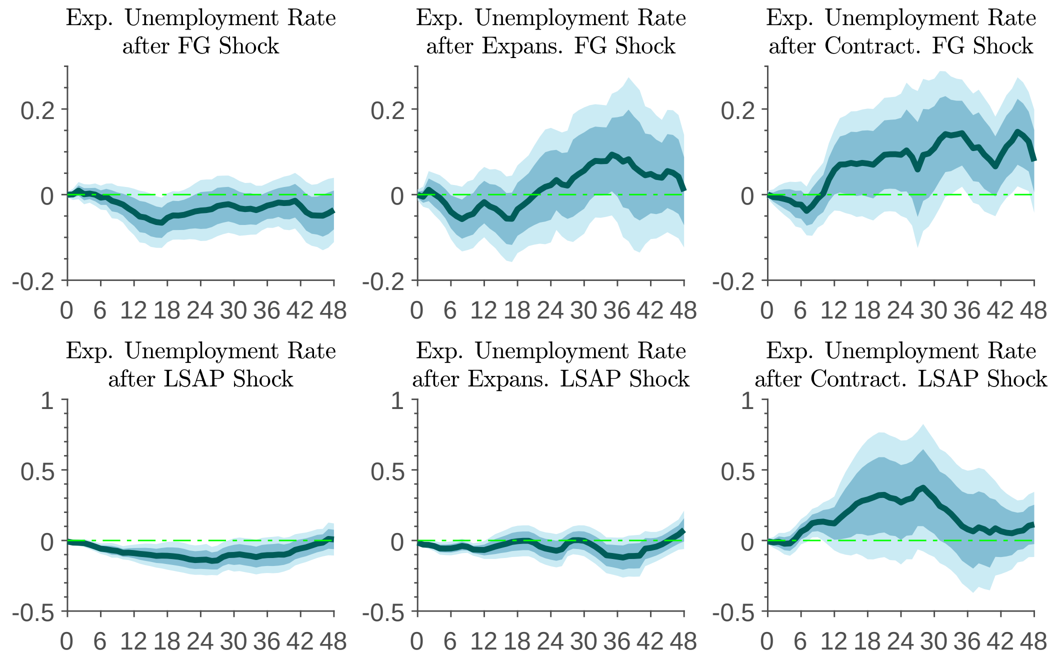

Figure 6: IRFs, Unemployment. The figure plots one-year-ahead expected unemployment rate response together with 68% and 90% confidence intervals.

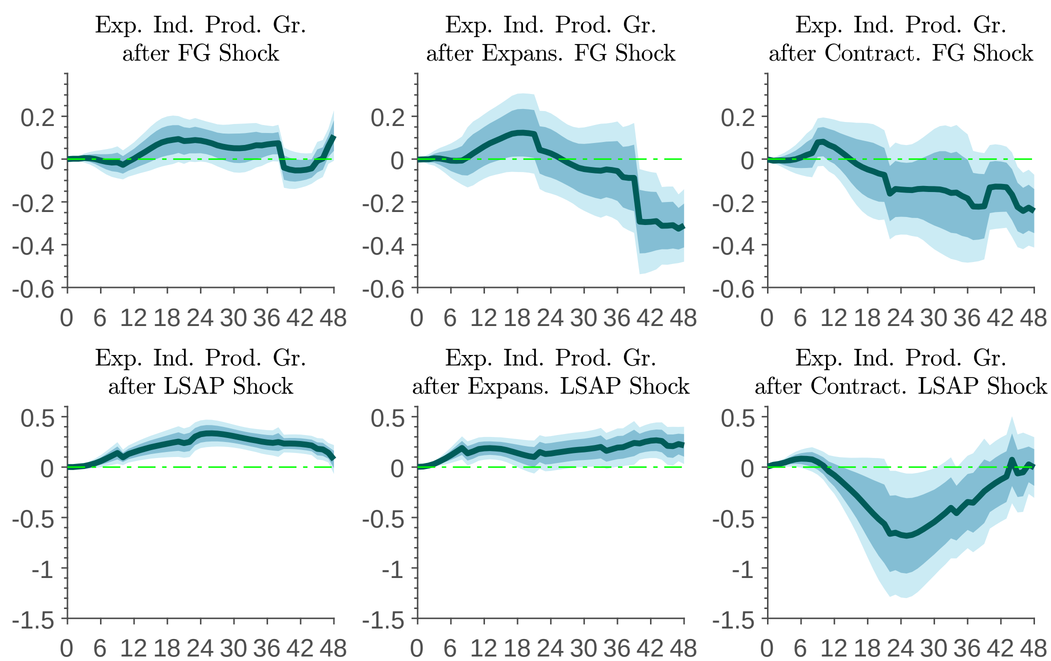

Figure 7: Cumulative IRFs, Industrial Production. The figure plots one-year-ahead expected Industrial Production response together with 68% and 90% confidence intervals.

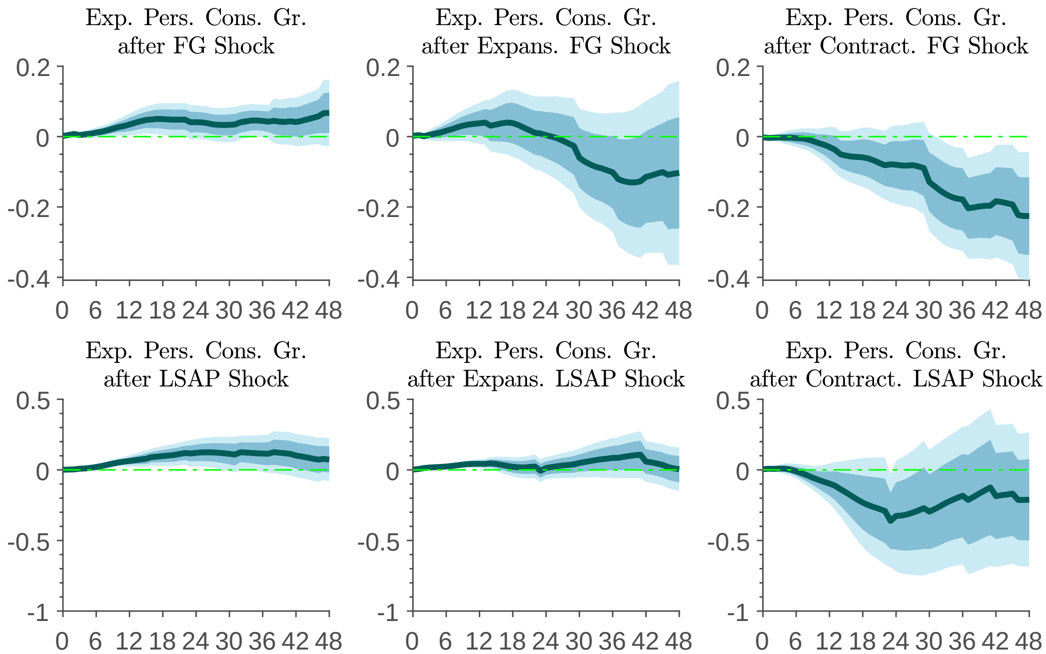

Figure 8: **Cumulative IRFs, Consumption.** The figure plots one-year-ahead expected personal consumption response together with 68% and 90% confidence intervals.

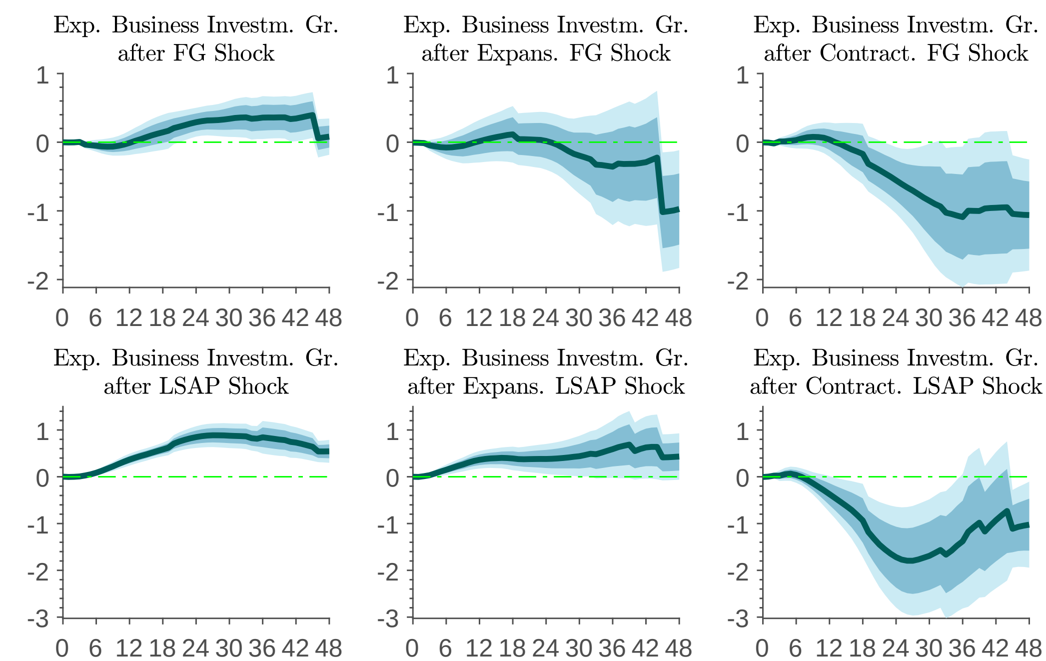

Figure 9: **Cumulative IRFs, Business Investment.** The figure plots one-year-ahead expected Business Investment response together with 68% and 90% confidence intervals.

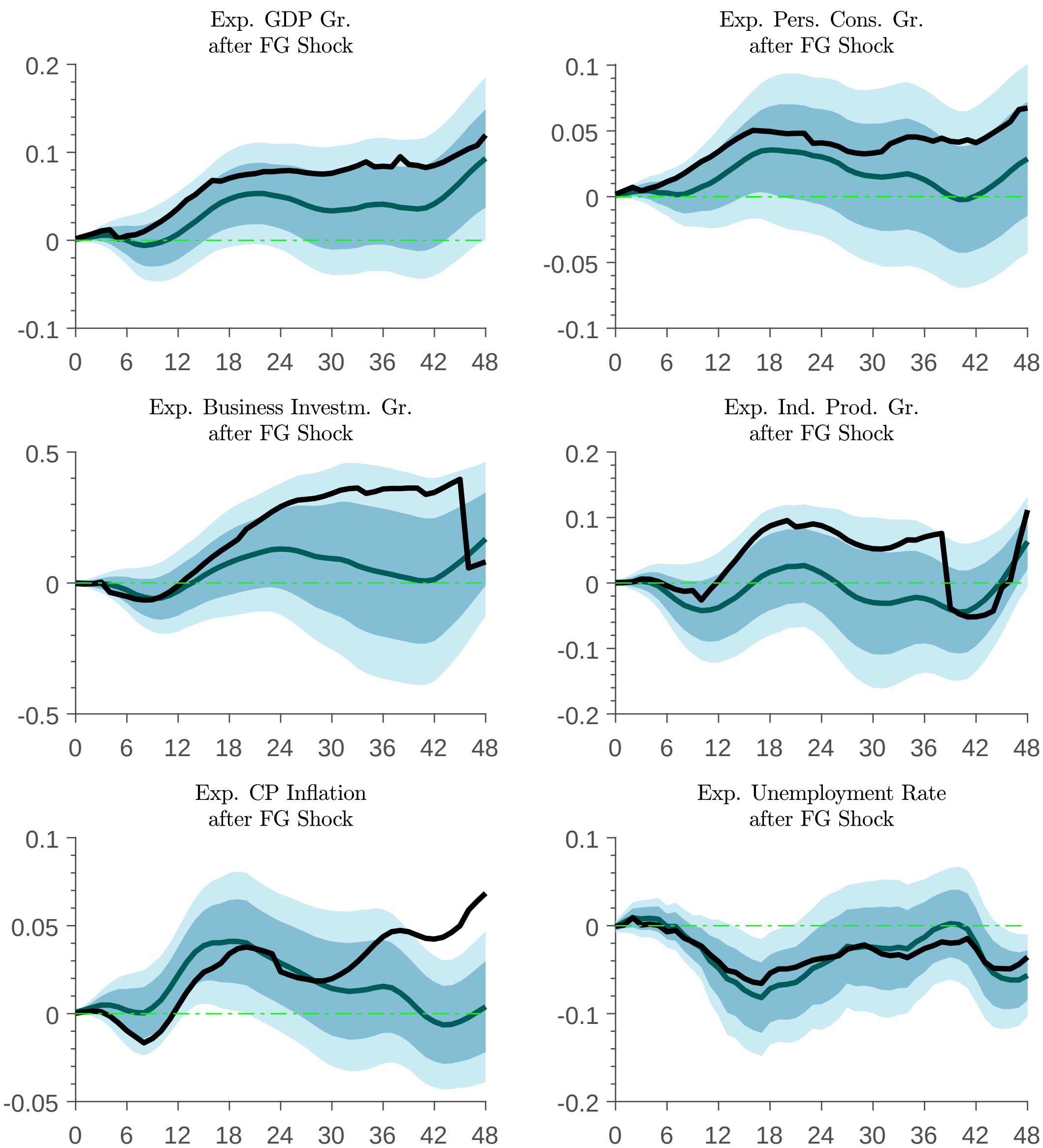

Figure 10: **IRFs Forward Guidance: automatic versus discretionary model selection.** The figure plots IRFs estimated from discretionary selection of the model (blue distribution) and the point-estimate IRFs from the corresponding model selected with our automatic procedure (black line), following a one standard deviation FG shock.

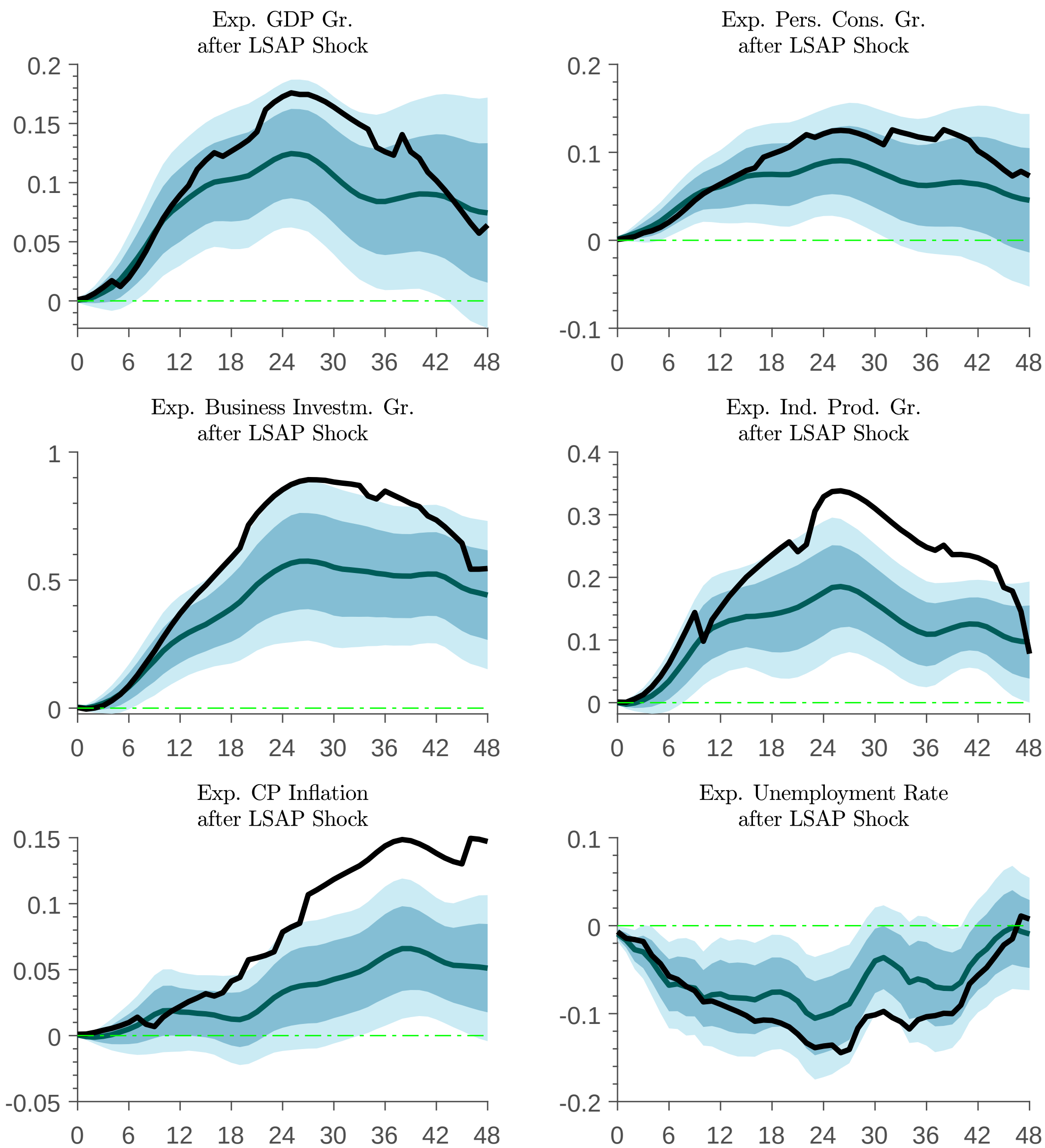

Figure 11: IRFs LSAP: automatic versus discretionary model selection. The figure plots IRFs estimated from discretionary selection of the model (blue distribution) and the point-estimate IRFs from the corresponding model selected with our automatic procedure (black line), following a one standard deviation LSAP shock.

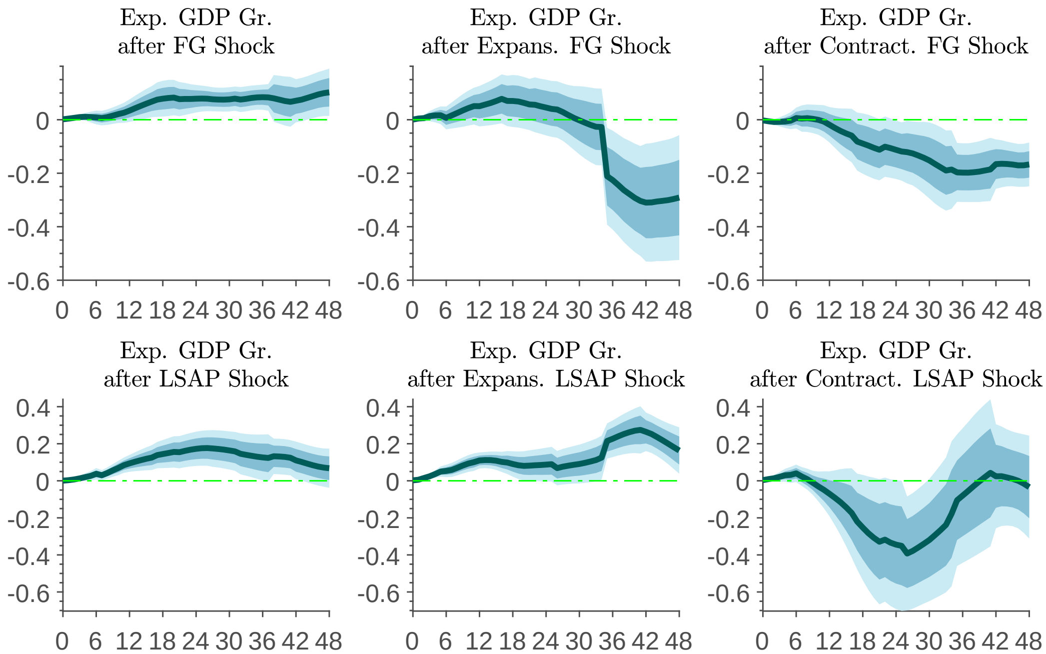

Figure 12: Cumulative IRFs, GDP. The figure plots one-year-ahead expected GDP response together with 68% and 90% confidence intervals. The information criterion is the AICu.

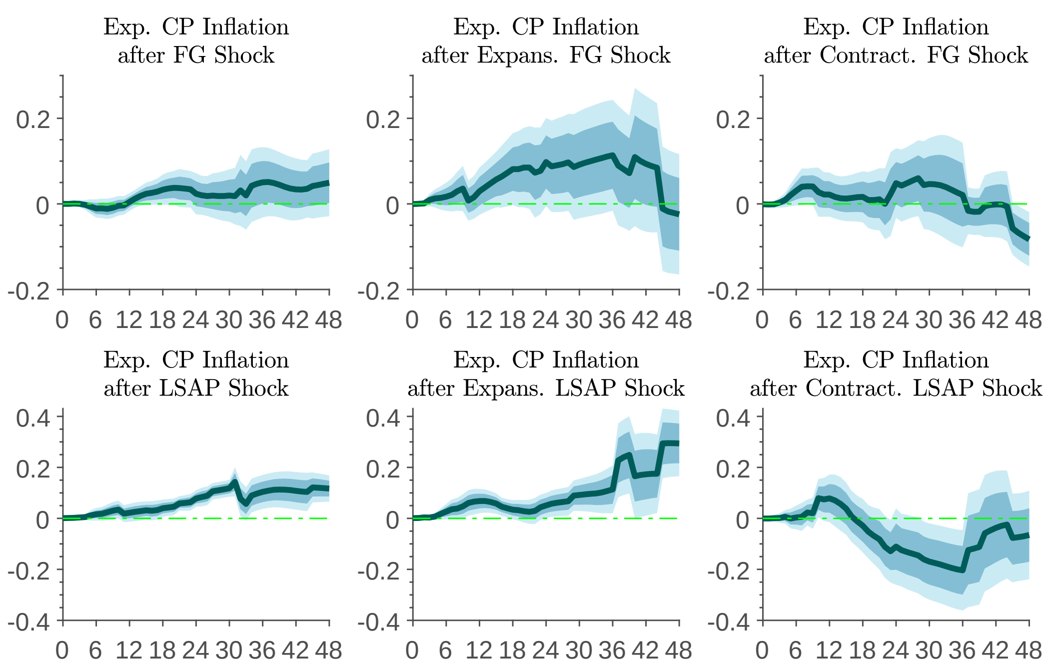

Figure 13: Cumulative IRFs, Inflation. The figure plots one-year-ahead expected CPI response together with 68% and 90% confidence intervals. The information criterion is the AICu.

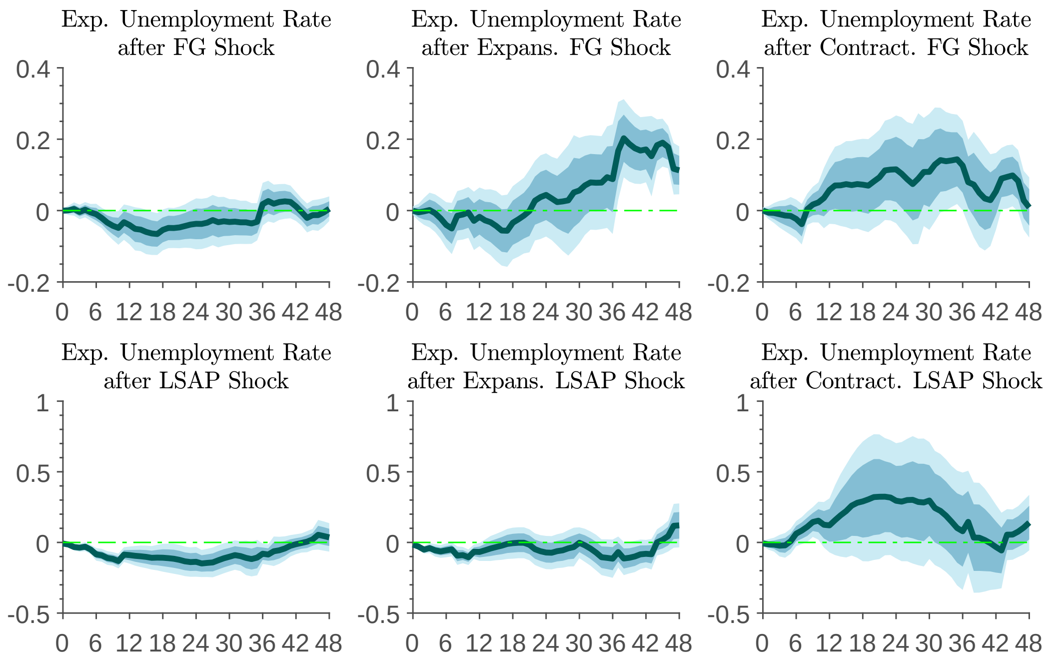

Figure 14: **IRFs, Unemployment.** The figure plots one-year-ahead expected unemployment rate response together with 68% and 90% confidence intervals. The information criterion is the AICu.

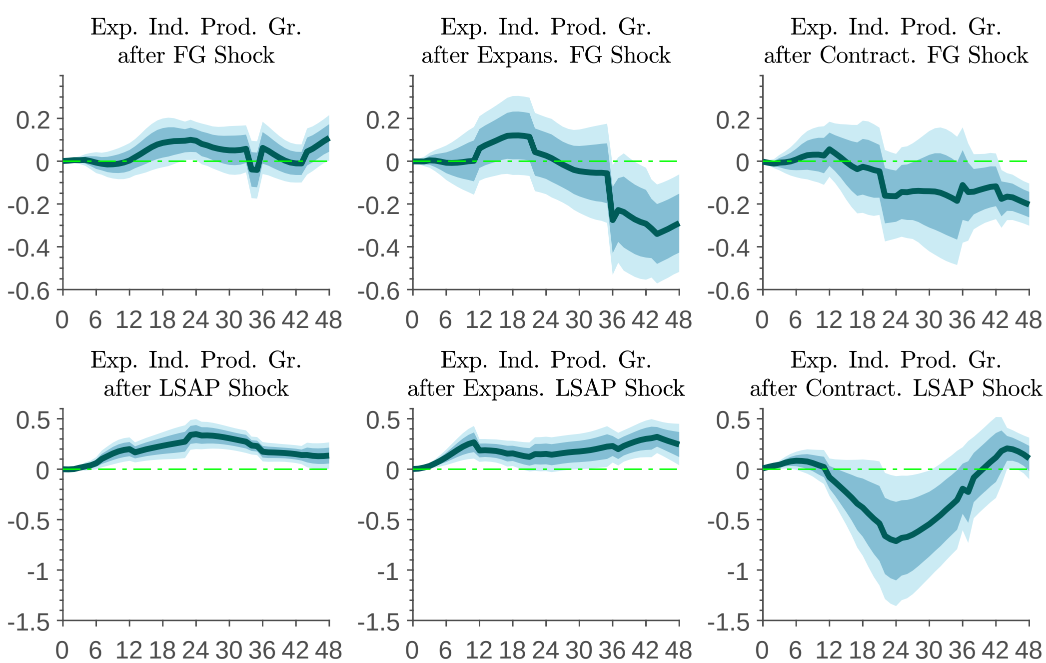

Figure 15: **Cumulative IRFs, Industrial Production.** The figure plots one-year-ahead expected Industrial Production response together with 68% and 90% confidence intervals. The information criterion is the AICu.

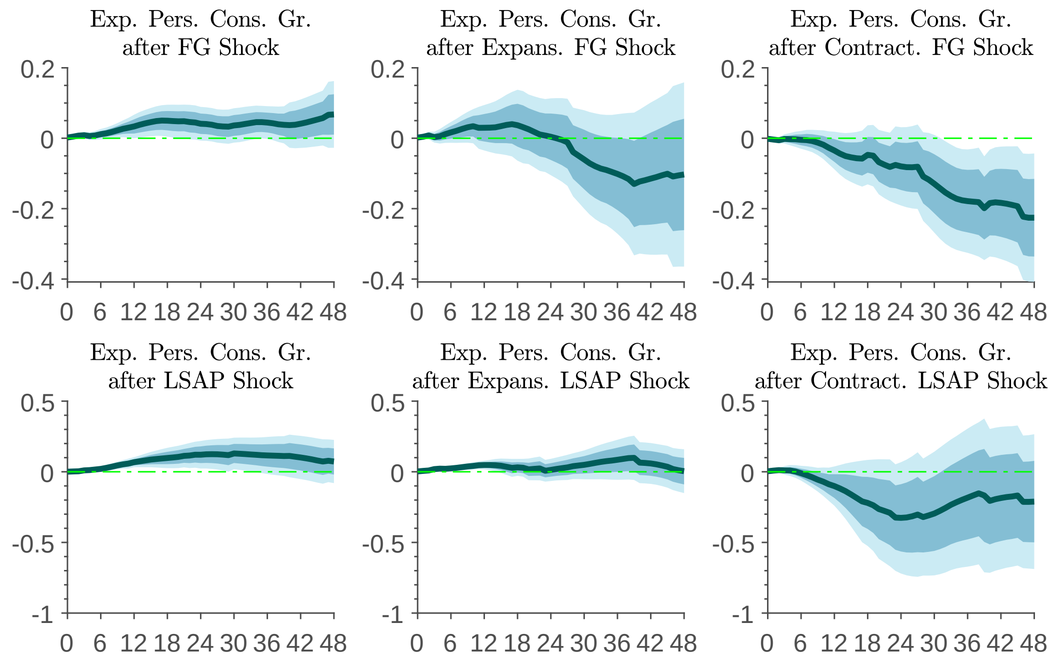

Figure 16: Cumulative IRFs, Consumption. The figure plots one-year-ahead expected personal consumption response together with 68% and 90% confidence intervals. The information criterion is the AICu.

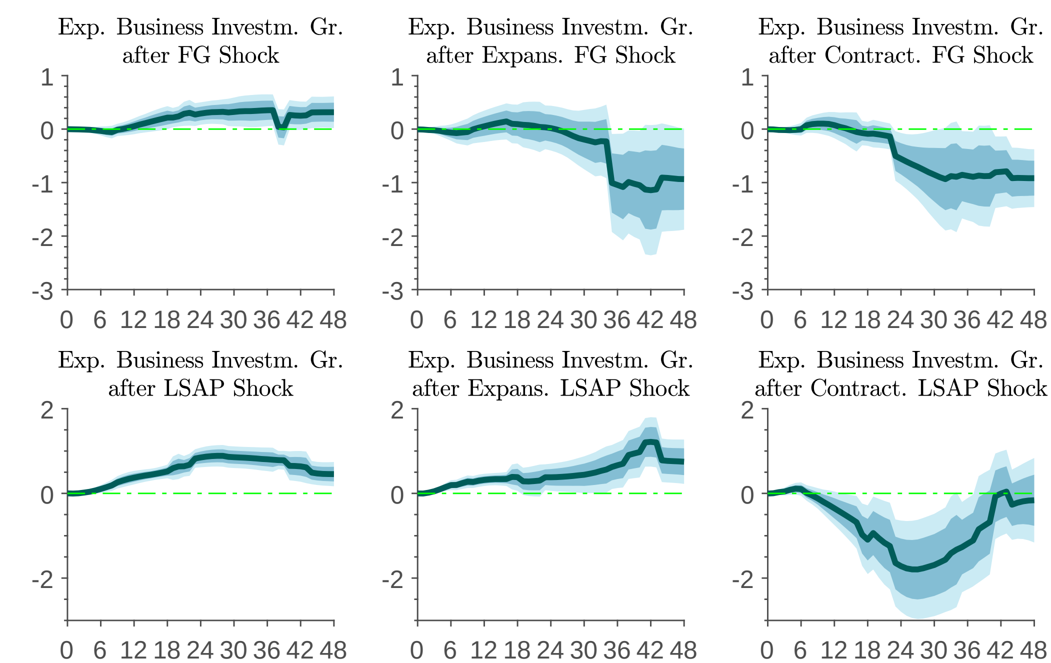

Figure 17: Cumulative IRFs, Business Investment. The figure plots one-year-ahead expected Business Investment response together with 68% and 90% confidence intervals. The information criterion is the AICu.

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