The Dynamic Effects of Forward Guidance Shocks Technical Appendix*

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A Data Description & Alternative VAR Results

A.1 Data Description

In our baseline VAR, we include the log levels of Macroeconomic Advisers' monthly real GDP series, its associated GDP deflator, and core capital goods shipments (non-defense capital goods excluding aircraft). The capacity utilization rate and the cumulatively-summed series of monetary policy surprises are included in the VAR in levels. To proxy for real investment at a monthly frequency, we deflate core capital goods shipments by the producer price index for capital equipment.

A.2 Alternative Ordering & Measures of Output

In this section, we report estimates of our empirical impulse responses with probability intervals from the robustness exercises in Figure 2 in the main text. Figure A.1 shows impulse responses when we order our policy surprise series first in our recursive VAR. This ordering interprets the policy surprises as predetermined with respect to macroeconomic aggregates. In Figure A.2, we further restrict the coefficients on lagged macroeconomic aggregates in our VAR model to be zero, thus treating the high-frequency policy surprises as exogenous shocks. Both figures share the same qualitative and quantitative features as Figure 1 of the main text which shows different assumptions regarding exogeneity and timing restrictions do not affect our empirical findings.

Figure A.3 shows our findings are robust if we replace the Macroeconomic Advisers monthly GDP and GDP deflater series with industrial production and the consumer price index (CPI). Gertler and Karadi (2015) measure output and prices at a monthly frequency using these variables. The findings suggest our qualitative understanding of the effects of forward guidance shocks is not sensitive to using these alternative measures of economic activity and prices.

A.3 Longer-Horizon Futures Contracts & Interest Rate Controls

In this section, we report estimates of our empirical impulse responses with probability intervals from the robustness exercises in Figure 3 in the main text. Figure A.4 shows impulse responses when we measure the forward guidance surprises using longer-dated Eurodollar futures. In our baseline VAR model in the main text, we measure policy expectations using one-year ahead federal funds futures rates. During the zero lower bound period, however, the

FOMC made several announcements concerning expected policy rates further than one year in the future.[1] Furthermore, Swanson and Williams (2014), Gertler and Karadi (2015), and Hanson and Stein (2015) argue the FOMC's forward guidance focused on managing interest-rate expectations over the next two years. Therefore, we now explore the robustness of our empirical results using longer-dated futures contracts. Figure A.4 shows that our findings are broadly similar to our baseline results if we instead use two-year ahead Eurodollar rates. Moreover, Figure A.5 shows that our results are unchanged if we also include the monthly average of the two-year Treasury rate in our baseline model.

Figure A.6 shows point estimates and the associated confidence intervals for a model which relies solely on the recursiveness assumption, rather than our high-frequency surprise series, to identify forward guidance shocks.[2] The VAR shown in Figure A.6 replaces the cumulative sum of our 12-month ahead surprise interest rate changes around FOMC meetings with the monthly average of the rate implied by the 12-month ahead federal funds futures contract. Therefore, this identification relies solely on the assumption that the Federal Reserve adjusted expected future policy rates in response to changing macroeconomic conditions and defines a forward guidance shock as the residual from this expected-rate reaction function.

While Figure A.6 shows we find very similar effects under this alternative identification scheme, we continue to favor our high frequency approach for several reasons. First, this approach is more restrictive with respect to exogeneity and timing restrictions. Unlike our baseline high-frequency approach, we can't examine alternative ordering schemes. A second reason we favor our high-frequency approach is its ability to shed light on the effects of forward guidance prior to the ZLB period. While the assumptions associated with a recursive

[1]For example, the August 2011 FOMC announcement indicated "exceptionally low levels of the federal funds rate at least through mid-2013." In January 2012, the FOMC used similar language to communicate that rates would be exceptionally low through "late 2014." Finally, the September 2012 statement indicated "low levels for the federal funds rate ... through mid-2015."

[2]The confidence intervals for this model, as well as the models which use the 8-quarter ahead Eurodollar rate or the GSS path factor during the ZLB period, are calculated using a rejection-sampling approach which rejects draws implying explosive dynamics. In computing the probability intervals for these models, we found these models featured a measurable number of parameter draws for the 90% level of significance that implied explosive dynamics. While our results regarding statistical significance of the impulse responses are unchanged if we rely on intervals that include these explosive draws, we find them economically uninteresting given the long-standing notion of long-run monetary neutrality. Moreover, we note that the VAR point estimates for all the models in the Appendix and the main text feature stable dynamics. If we reduce the level of significance from 90% to 68%, we find no evidence of explosive dynamics, which suggests this issue stems from the difficulty of accurately measuring probability intervals at the 95th and 5th percentile (this is one reason why Sims and Zha (1999) recommend 68% posterior intervals).

VAR feature futures rates are plausible during the ZLB period, they are harder to justify in the Pre-ZLB period where the target funds rate, rather than expected rates, was often the assumed instrument adjusted in response to macroeconomic conditions.

Figure A.7 shows point estimates and the associated confidence intervals for a model which uses the Gurkaynak, Sack and Swanson (2005) style path factor to measure forward guidance shocks during the zero lower bound period. In the main text, Figure 7 shows point estimates for this model. Figure A.7 confirms that using interest rate futures data extending up to 8-quarters ahead delivers responses to a forward guidance shock consistent with our baseline model (See Appendix Section D.4 for details on the construction of this path factor) .

A.4 Additional Lags

In our baseline empirical model, both the AIC and SBIC information criterions recommend the use of one lag in our VAR. However, our results are not sensitive to the inclusion of additional lags. Figure A.8 shows impulse responses to a forward guidance shock are nearly unchanged if we instead use two lags in our empirical model. Since we estimate our VAR in levels, a two-lag model can recover any first-order relationship in differences, so it is reassuring that our level VAR results are unchanged if we include a second lag. The primary issue limiting the number of lags we can include in the VAR is sample size. A common rule of thumb is to include 12 lags in a monthly VAR. However, our 5 variable VAR with 12 lags would include 300 free parameters (not counting intercepts and error variance-covariance terms) while we have less than 100 observations for each series during the ZLB period. Therefore, in Figure 8 of the main text, we extend our sample to include pre-ZLB data and use a rule-of-thumb lag selection of 12 lags for our monthly VAR. Under this longer sample with additional lags, we find qualitatively similar results regarding the macroeconomic effects of forward guidance.

B Model

In the symmetric equilibrium, the baseline model in Dynare notation is as follows:

```
model;

// Private Sector

y  = pd^(-1)*n^(1 - alpha)*(u*k(-1))^(alpha);
y  = c + inv;
w  = chi*(a/lambda)*n^(eta);
lambda  = a * (c - b*c(-1))^(-1);
1  = beta * (lambda(+1)/lambda) * ( r/pie(+1) );
1  = beta * (lambda(+1)/lambda) * ( rr );

w  = (1 - alpha)*(y*pd/n)/mu;
rrk*u  = alpha*(y*pd/k(-1))/mu;
q*deltauprime*k(-1) = alpha*(y*pd/u)/mu;
k  = (1 - deltau)*k(-1) + inv*( 1 - (phii/2)*(inv/inv(-1)-1)^(2) );
deltau = delta0 + delta1*(u-1) + (delta2/2)*(u-1)^(2);
deltauprime = delta1 + delta2*(u-1);

g1 = lambda*y/mu
+ omega*beta*(pie(+1)/(piess^(1-gamma)*pie^gamma))^(theta)*g1(+1);
g2 = piestar*(lambda*y
+ omega*beta*((pie(+1)/(piess^(1-gamma)*pie^gamma))^(theta-1)/piestar(+1))*g2(+1));

1 = omega*(pie/(piess^(1-gamma)*pie(-1)^gamma))^(theta-1)
+ (1-omega)*(piestar^(1-theta));
pd = omega*(pie/(piess^(1-gamma)*pie(-1)^gamma))^(theta)*pd(-1)
+ (1-omega)*piestar^(-theta);

theta*g1 = (theta-1)*psi*g2;

1 - q*(1 - (phii/2)*(inv/inv(-1)-1)^(2) - phii*(inv/inv(-1)-1)*(inv/inv(-1)) )
= beta * q(+1) * (lambda(+1)/lambda) * phii * (inv(+1)/inv - 1)*(inv(+1)/inv)^(2);
q  = beta * (lambda(+1)/lambda) * ( rrk(+1)*u(+1) + q(+1) * (1 - deltau(+1)) );
```

```
a   = (1-rhoa)*ass + rhoa * a(-1) + vola*ea;
nu   = rhonu * nu(-1) + volnu*enu;

// Lagged Expectations

expy1 = y(+1);
lagey = expy1(-1);
expinv1 = inv(+1);
lageinv = expinv1(-1);
expu1 = u(+1);
lageu = expu1(-1);
exppie1 = pie(+1);
lagepie = exppie1(-1);
expc1 = c(+1);
lagec = expc1(-1);

// Monetary Policy Rule

log(rd)  = phir*log(rd(-1))
+ (1-phir) * (log(rss)  + phipie*log(lagepie/piess) + phix*log(lagey/yss)) + nu;

r = rd;

// Futures Rates

1  = beta * (lambda(+1)/lambda) * ( r/pie(+1) ) * ( 1 - 12*log(r(+1)) ) / f1;
1  = beta * (lambda(+1)/lambda) * ( r/pie(+1) ) * f1(+1) / f2;
1  = beta * (lambda(+1)/lambda) * ( r/pie(+1) ) * f2(+1) / f3;
1  = beta * (lambda(+1)/lambda) * ( r/pie(+1) ) * f3(+1) / f4;
1  = beta * (lambda(+1)/lambda) * ( r/pie(+1) ) * f4(+1) / f5;
1  = beta * (lambda(+1)/lambda) * ( r/pie(+1) ) * f5(+1) / f6;
1  = beta * (lambda(+1)/lambda) * ( r/pie(+1) ) * f6(+1) / f7;
1  = beta * (lambda(+1)/lambda) * ( r/pie(+1) ) * f7(+1) / f8;
1  = beta * (lambda(+1)/lambda) * ( r/pie(+1) ) * f8(+1) / f9;
1  = beta * (lambda(+1)/lambda) * ( r/pie(+1) ) * f9(+1) / f10;
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```
1  = beta * (lambda(+1)/lambda) * ( r/pie(+1) ) * f10(+1) / f11;
1  = beta * (lambda(+1)/lambda) * ( r/pie(+1) ) * f11(+1) / f12;

expr1f = 1 - f1;
expr2f = 1 - f2;
expr3f = 1 - f3;
expr4f = 1 - f4;
expr5f = 1 - f5;
expr6f = 1 - f6;
expr7f = 1 - f7;
expr8f = 1 - f8;
expr9f = 1 - f9;
expr10f = 1 - f10;
expr11f = 1 - f11;
expr12f = 1 - f12;

end;
```

Since the capital stock is predetermined, we lag the capital stock K variables by one period relative to the timing in the model derivation.

C Additional IRF Matching Results

This section presents additional results from our IRF matching procedure we use to estimate the model parameters. In our baseline model, we find much larger monthly investment adjustment costs than the quarterly estimates of Christiano, Eichenbaum and Evans (2005). Large adjustment costs imply that firms make incremental investments in their capital stock which generates persistence in the response of investment and overall output. Thus, the model prefers a large value of κ as it helps the model account for the persistence of output and investment we find in the data. Figure C.1 and Table C.1 shows the results for an alternative prior over κ which governs the cost of adjusting investment. In this alternative prior, we keep the prior mode centered at the estimates in Christiano, Eichenbaum and Evans (2005) but reduce our prior variance such that it equals the standard deviation of the parameter estimate from Christiano, Eichenbaum and Evans (2005). Under this alternative prior, the model's fit deteriorates a bit, but not significantly, with the primary difference being the persistence of the investment and output responses. When we instead estimate a quarterly version of our model on time-aggregated empirical impulse responses, we find an estimate of κ not significantly different from Christiano, Eichenbaum and Evans (2005) which suggests that the monthly- to quarterly-frequency mapping of κ is highly nonlinear. Therefore, the large value of κ we estimate in the monthly model doesn't seem unreasonable.

Figure C.2 and Table C.1 also show the results for alternative priors over ϕ_r, the degree of smoothing in the desired policy rate also discussed in Section 4.3 of the main text. We explore two alternative priors to our baseline prior mode of 0.75 for ϕ_r, one centered at 0.25 and one at 0.95. In both cases, we find the model fit is very similar to our baseline results with the posterior modes of ϕ_r very close to each respective prior mode. These results show that the overall fit of our model does not rely on a particular assumption regarding the amount of history dependence in the central bank's policy rule.

D Data Appendix

This appendix details how we use interest rate futures contracts to derive implied measures of expected future interest rates. In the paper, we use federal funds futures contracts and Eurodollar futures contracts. Below, we detail how we use each type of interest rate futures contract to extract various measures of investor's interest-rate expectations.

D.1 Unscaled Federal Funds Futures Contracts

Federal funds futures contracts settle based on the average of the daily effective federal funds rate during the contract expiration month. We obtain daily data on the closing price of federal funds futures contracts obtained from the Chicago Mercantile Exchange (CME). Let p_t^j denote the price at time t of the federal funds futures contract expiring j months ahead. The time t expectation of the average effective federal funds rate rate implied by the futures contract expiring j months ahead is $f_t^j = 100 - p_t^j$. Then the surprise component of the j month ahead expected policy rate emanating from the FOMC meeting occurring on date t, is:

$$m_t^j = f_t^j - f_{t-1}^j. \tag{1}$$

In our baseline VAR models, the cumulative sum of m_t^{12} is our baseline measure of forward guidance surprises during the zero lower bound period.

D.2 Scaled Federal Funds Futures Contracts

Another common approach to measuring changes in expectations regarding the future path of policy rates is to measure policy surprises at an FOMC meeting frequency. Since FOMC meetings typically occur in the middle of the month, this approach requires taking account of the date of the meeting relative to the number of days in the month to extract the expected federal funds rate changes at future FOMC meetings. The method and notation below for extracting what we refer to as scaled policy surprises follows from Gurkaynak (2005). In practice, we found essentially no differences in our VAR results when using the scaled or unscaled surprises. However, to be consistent with Gurkaynak, Sack and Swanson (2005) when forming our path factor we use scaled policy surprises.

Let $p_t^{i(j)}$ denote the price at time t of the federal funds futures contract expiring in month $i(j)$, where $j = 0, 1, 2, ...$ indexes the current to the 7th-upcoming FOMC meeting, and $i(j)$ denotes the month of the j-th upcoming meeting. The time t expectation of the average effective federal funds rate rate implied by the futures contract expiring $i(j)$ months ahead is $f_t^{i(j)} = 100 - p_t^{i(j)}$. Finally, let d_j denote the day of the month of the j-th upcoming FOMC meeting and m_j denote the total number of days in the month in which the j-th next FOMC meeting takes place.

Surprise Component of the Current Target Federal Funds Rate

The day before the current FOMC meeting, the spot-month federal funds future contract satisfies:

$$f_{t-1}^0 = \frac{d_0}{m_0} r_{-1} + \frac{m_0 - d_0}{m_0} E_{t-1}(r_0) + \mu_{t-1}^0, \tag{2}$$

where r_{-1} is the annualized target federal funds rate prevailing before the meeting (which is assumed to equal the effective federal funds rate each day of the month before the meeting) and r_0 is the annualized target federal funds rate after the meeting the next day. The term μ_{t-1}^0 is the term-premium for the spot-month federal funds futures contract which we assume is constant between the day before and the day of the FOMC meeting.

The next day after the FOMC's rate decision, at time t, the spot-month federal funds future contract satisfies:

$$f_t^0 = \frac{d_0}{m_0} r_{-1} + \frac{m_0 - d_0}{m_0} r_0 + \mu_t^0. \tag{3}$$

Combining Equations 2 and 3, the unexpected policy surprise in the target federal funds rate is, denoted by e_t^0, is defined by:

$$e_t^0 \equiv r_0 - E_{t-1}(r_0) = \left[\left(f_t^0 - f_{t-1}^0\right) - \left(\mu_t^0 - \mu_{t-1}^0\right)\right] \frac{m_0}{m_0 - d_0} = \left(f_t^0 - f_{t-1}^0\right) \frac{m_0}{m_0 - d_0} \tag{4}$$

where the last equality follows from the assumption that the term-premium for the spot-month federal funds futures contract is constant between the day before and the day of the FOMC meeting. In practice, this assumption is reasonable except for meetings late in the month for which any small change in term-premia between the day-before and the day-of the FOMC meeting would be magnified by $m_0/(m_0 - d_0)$. To get around this large scaling factor, anytime the scale factor – $m_0/(m_0 - d_0)$ – is greater than 4, we use the next month's contract instead of the current month contract. In this case, $e_t^0 = f_t^1 - f_{t-1}^1$ since for meetings late in a month there is no meeting the subsequent month.

Surprise Component of the Funds Rate Expected at 1st-Upcoming Meeting

While e_t^0 captures the monetary policy surprise generated by changes in the current target federal funds rate, forward guidance influences expectations about the future path of the federal funds rate. Therefore, to extract policy surprises in the future path of interest rates, we assume investors know the dates of future FOMC meetings and we extract how their expectations of rate changes evolve around each FOMC meeting. The day before the current FOMC meeting, the federal funds future contract expiring $i(1)$ months ahead, which is the month of the 1st-upcoming FOMC meeting, satisfies:

$$f_{t-1}^{i(1)} = \frac{d_1}{m_1} E_{t-1}(r_0) + \frac{m_1 - d_1}{m_1} E_{t-1}(r_1) + \mu_{t-1}^1, \tag{5}$$

where r_0 is the annualized target federal funds rate rate set after the current meeting (which takes place the next day) and r_1 is the annualized target federal funds rate rate set after the first next meeting (which takes place $i(1)$ months in the future). The term μ_{t-1}^1 is the term-premium for the federal funds futures contract expiring $i(1)$ months ahead, which is assumed to be constant between the day before and the day of the FOMC meeting.

The next day after the FOMC issues its statement and any possible forward guidance at time t, the federal funds future contract expiring $i(1)$ months ahead, which is the month in which the 1st-upcoming FOMC meeting takes place, satisfies:

$$f_t^{i(1)} = \frac{d_1}{m_1} E_t(r_0) + \frac{m_1 - d_1}{m_1} E_t(r_1) + \mu_t^1. \tag{6}$$

Combining Equations 5 and 6, the unexpected policy surprise in the federal funds rate expected to prevail after the 1st next FOMC meeting, denoted by e_t^1, is defined by:

$$e_t^1 \equiv E_t(r_1) - E_{t-1}(r_1) = \left[\left(f_t^{i(1)} - f_{t-1}^{i(1)} \right) - \frac{d_1}{m_1} e_t^0 \right] \frac{m_1}{m_1 - d_1} \tag{7}$$

where the last equality follows from the assumption that the term-premium for the federal funds futures contract expiring $i(1)$ months ahead is constant between the day before and the day of the FOMC meeting. Once again, anytime the scale factor – $m_1/(m_1 - d_1)$ – is greater than 4, we use the next month's contract, which implies $e_t^1 = f_t^{i(1)+1} - f_{t-1}^{i(1)+1}$.

Surprise Component of the Funds Rate Expected at j-th Upcoming Meeting

Following this same recursion, the unexpected policy surprise in the federal funds rate expected to prevail after the j-th next FOMC meeting, denoted by e_t^j, is defined by:

$$e_t^j \equiv E_t(r_j) - E_{t-1}(r_j) = \left[\left(f_t^{i(j)} - f_{t-1}^{i(j)} \right) - \frac{d_j}{m_j} e_t^{j-1} \right] \frac{m_j}{m_j - d_j}, \tag{8}$$

where r_j is the annualized target federal funds rate rate set after the j-th next meeting (which takes place $i(j)$ months in the future). Once again, anytime the scale factor – $m_j/(m_j - d_j)$ – is greater than 4, we use the next month's contract, which implies $e_t^j = f_t^{i(j)+1} - f_{t-1}^{i(j)+1}$.

D.3 Eurodollar Futures Contracts

Unlike federal funds futures contracts, USD Eurodollar futures contracts don't settle based on the average of their underlying instrument during the settlement month. Therefore, there is no scaling necessary when using these interest rate futures contracts to extract expectations about the future path of monetary policy.

Surprise Component of the Funds Rate Implied by Eurodollar Futures

We obtain daily data on the closing price of USD Eurodollar futures contracts from the CME Group with contracts maturing $i = 6, 9, 12, 15, 18, 21, 24, 27$ months into the future. Let r_i denote the annualized 3-month USD LIBOR interest rate on the third Wednesday i months in the future. Also, let $p_t^{x,i}$ denote the time t closing price of the Eurodollar contract expiring i months in the future and $f_t^{x,i} = 100 - p_t^{x,i}$ denote the implied rate. Then, the unexpected policy surprise, as implied by the Eurodollar contract maturing i months in the future, emanating from the FOMC meeting occurring at time t, is:

$$x_t^i \equiv E_t(r_i) - E_{t-1}(r_i) = f_t^{x,i} - f_{t-1}^{x,i}. \tag{9}$$

D.4 Gurkaynak, Sack, and Swanson (2005) Path Factor

In the paper, we compute the Gurkaynak, Sack and Swanson (2005) path factor which uses principal component analysis to compress all of the information from numerous interest rate futures contracts into a single indicator of forward guidance. To generate the Gurkaynak, Sack and Swanson (2005) path factor, we standardize e^0, e^1, x_t^6, x_t^9, x_t^{12}, x_t^{15}, x_t^{18}, x_t^{21}, x_t^{24}, x_t^{27} such that each series has a mean of zero and a standard deviation of one. Then, we extract the first two principle components of these 10 time-series, denoted by f^1 and f^2, over the sample January 1994 to December 2015. Next, we standardize f^1 and f^2 and then calculate the loading of e^0 on the standardized f^1 and f^2 by running the OLS regressions $e_t^0 = \gamma_1 f_t^1 + \epsilon_t$ and $e_t^0 = \gamma_2 f_t^2 + \epsilon_t$.

With the factor loadings γ_1 and γ_2 in hand, we transform f^1 and f^2 into z^1 (the target factor) and z^2 (the path factor) using the linear transformation:

$$\begin{bmatrix} z^1 & z^2 \end{bmatrix} = \begin{bmatrix} f^1 & f^2 \end{bmatrix} \begin{bmatrix} \alpha_1 & \beta_1 \\ \alpha_2 & \beta_2 \end{bmatrix}. \tag{10}$$

The matrix elements $\alpha_1, \alpha_2, \beta_1, \beta_2$ are identified from the four restrictions:

Restrictions 1 and 2: The columns of the transforming matrix have unit length (so that the target and path factors have a standard deviation of 1).

$$\alpha_1^2 + \alpha_2^2 = 1$$
$$\beta_1^2 + \beta_2^2 = 1$$

Restriction 3: The target and path factors remain orthogonal after the transformation.

$$E(z^1 z^2) = \alpha_1\beta_1 + \alpha_2\beta_2 = 0$$

Restriction 4: The path factor has no influence on the current policy surprise e^0. Since,

$$f^1 = \frac{1}{\alpha_1\beta_2 + \alpha_2\beta_1}[\beta_2 z^1 - \alpha_2 z^2]$$
$$f^2 = \frac{1}{\alpha_1\beta_2 + \alpha_2\beta_1}[\alpha_1 z^2 - \beta_2 z^1],$$

then the effect of a change in z^2 on e^0 is defined by:

$$\frac{de^0}{dz^2} = \frac{de^0}{df^1}\frac{df^1}{dz^2} + \frac{de^0}{df^2}\frac{df^2}{dz^2} = -\gamma_1\frac{\alpha_2}{\alpha_1\beta_2 + \alpha_2\beta_1} + \gamma_2\frac{\alpha_1}{\alpha_1\beta_2 + \alpha_2\beta_1} = 0$$

This implies the parameter restriction that: $\gamma_2\alpha_1 = \gamma_1\alpha_2$.

Finally, we rescale the resulting z^1 and z^2 vectors. We scale the target factor so that e^0 has a one-for-one effect on it by regressing $e_t^0 = \beta z_t^1 + \epsilon_t$ and then setting $z^{target} = \beta z^1$. Then, we scale the path factor so that it has the same magnitude effect on x^{18} as z^{target} by regressing $x_t^{18} = \beta_{target} z_t^{target} + \epsilon_t$ and $x_t^{18} = \beta_{path} z_t^2 + \epsilon_t$ and then setting $z^{path} = \beta_{path}/\beta_{target} z^2$.

References

Christiano, Lawrence J., Martin Eichenbaum, and Charles L. Evans. 2005. "Nominal Rigidities and the Dynamic Effects of a Shock to Monetary Policy." *Journal of Political Economy*, 113(1): 1–45.

Gertler, Mark, and Peter Karadi. 2015. "Monetary Policy Surprises, Credit Costs, and Economic Activity." *American Economic Journal: Macroeconomics*, 7(1): 44–76.

Gurkaynak, Refet S. 2005. "Using Federal Funds Futures Contracts for Monetary Policy Analysis." Working Paper.

Gurkaynak, Refet S, Brian Sack, and Eric Swanson. 2005. "Do Actions Speak Louder Than Words? The Response of Asset Prices to Monetary Policy Actions and Statements." *International Journal of Central Banking*, 1(1): 55–93.

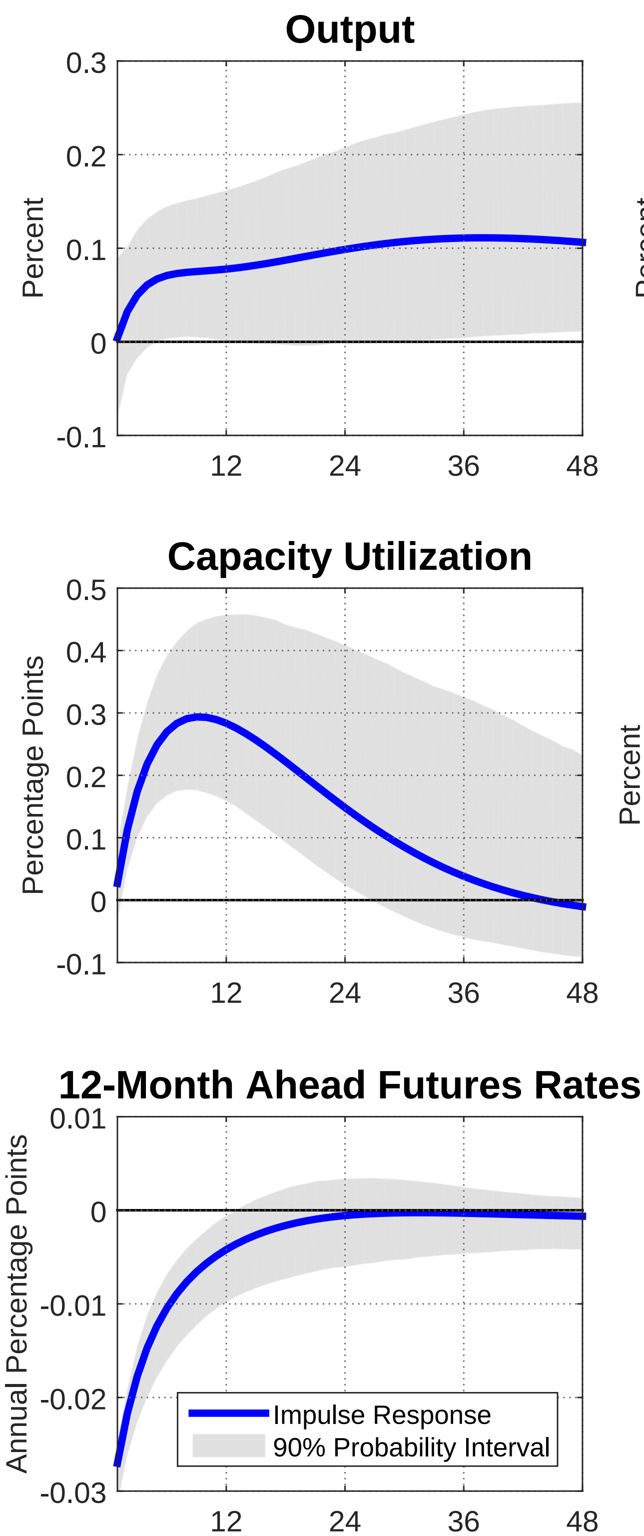
Hanson, Samuel G, and Jeremy C Stein. 2015. "Monetary Policy and Long-Term Real Rates." *Journal of Financial Economics*, 115(3): 429–448.

Romer, Christina D., and David H. Romer. 2004. "A New Measure of Monetary Shocks: Derivation and Implications." *American Economic Review*, 94(4): 1055–1084.

Sims, Christopher A., and Tao Zha. 1999. "Error Bands for Impulse Responses." *Econometrica*, 67(5): 1113–1155.

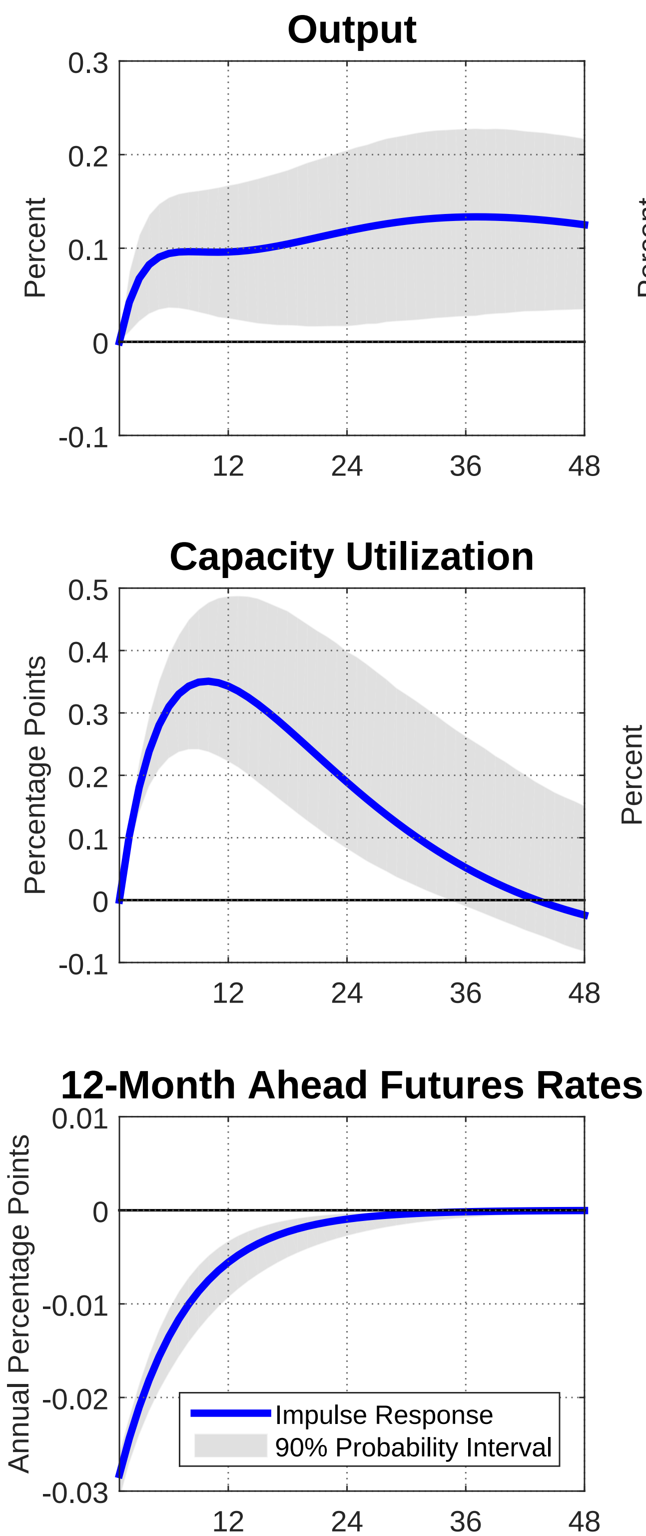
Swanson, Eric T., and John C. Williams. 2014. "Measuring the Effect of the Zero Lower Bound on Medium- and Longer-Term Interest Rates." *American Economic Review*, 104(10): 3154–85.

Figure A.1: Empirical Impulse Responses with Policy Ordered First



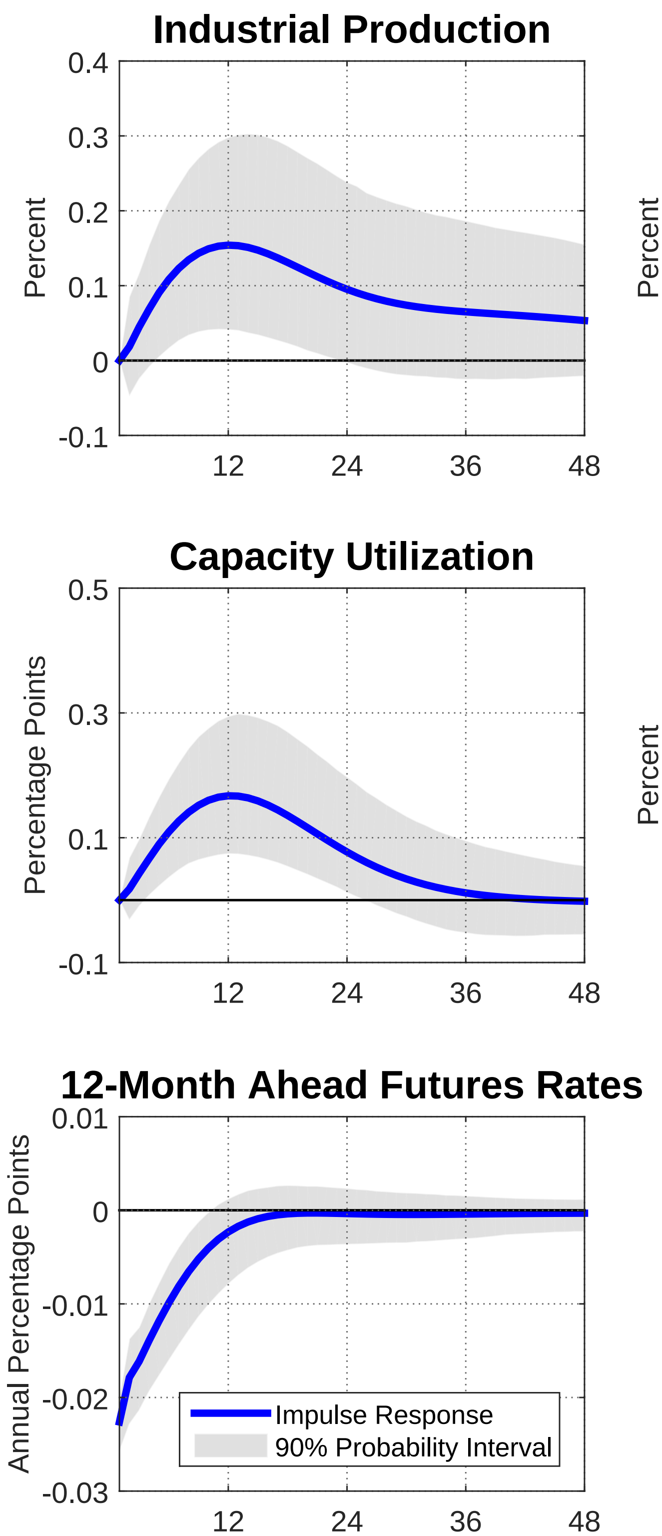
Note: The solid blue lines denote the empirical point estimate to a one standard deviation shock and the shaded areas denote the 90% probability interval of the posterior distribution.

Figure A.2: Empirical Impulse Responses with Policy Surprises Treated as Exogenous



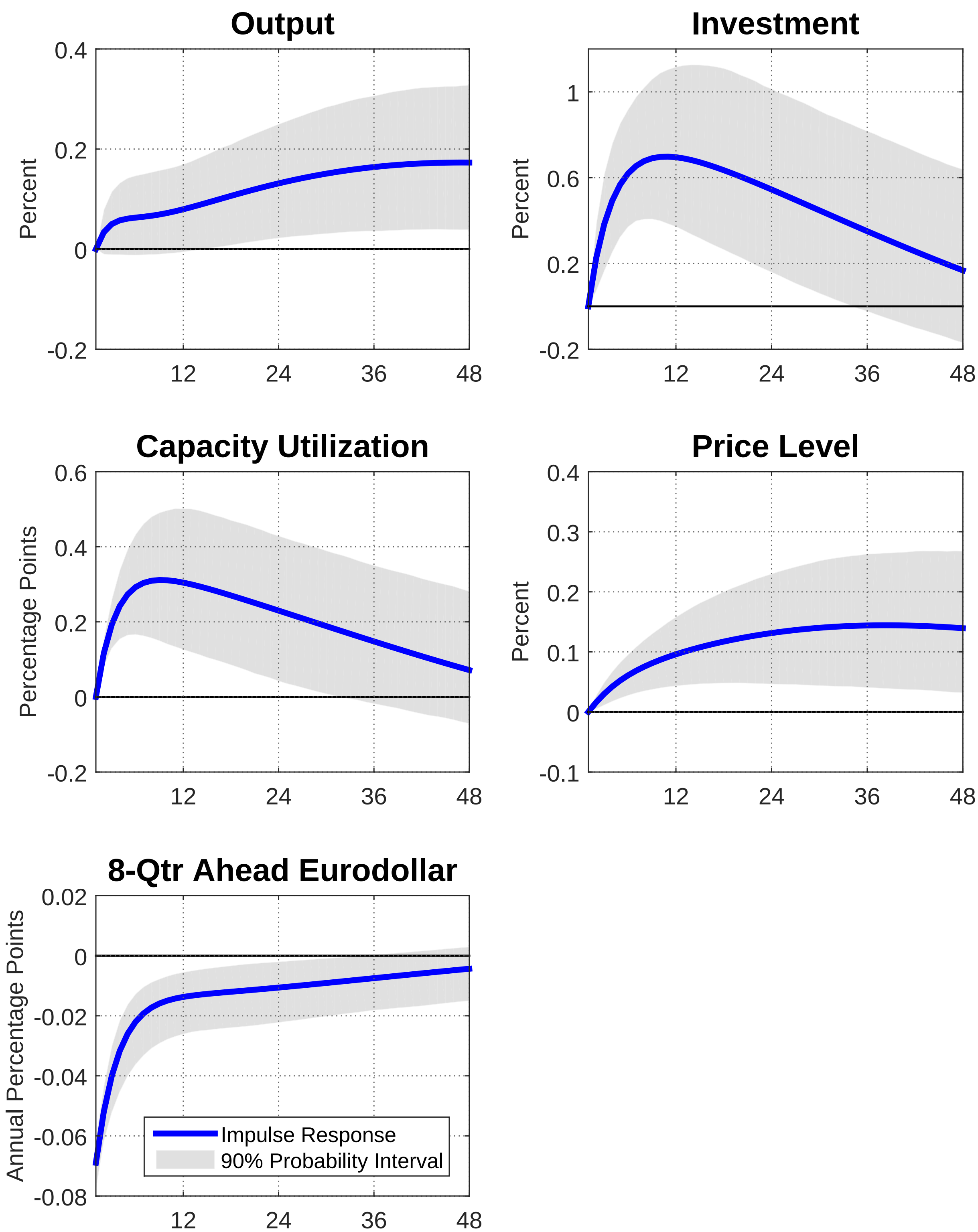
Note: The solid blue lines denote the empirical point estimate to a one standard deviation shock and the shaded areas denote the 90% probability interval of the posterior distribution.

Figure A.3: Empirical Impulse Responses using Industrial Production & CPI



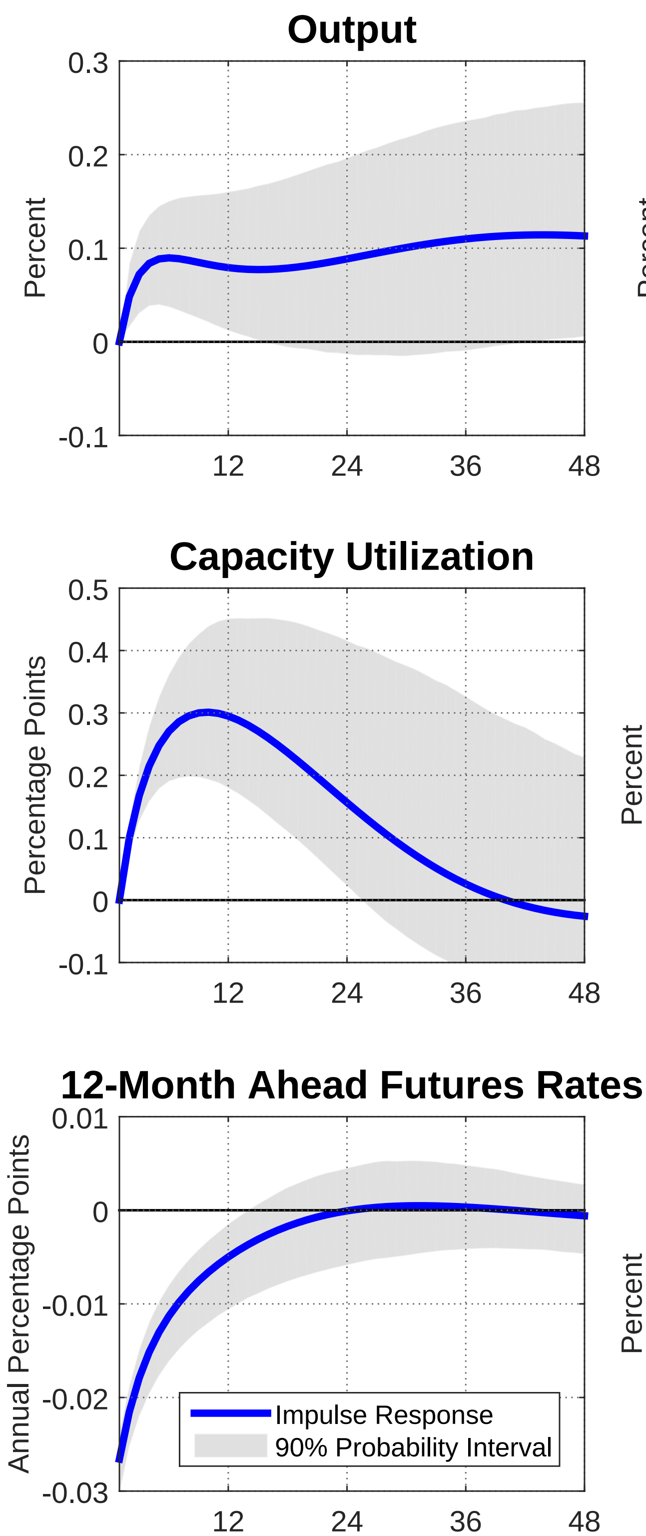
Note: The solid blue lines denote the empirical point estimate to a one standard deviation shock and the shaded areas denote the 90% probability interval of the posterior distribution.

Figure A.4: Empirical Impulse Responses using 8-Quarter Ahead Eurodollar Rates



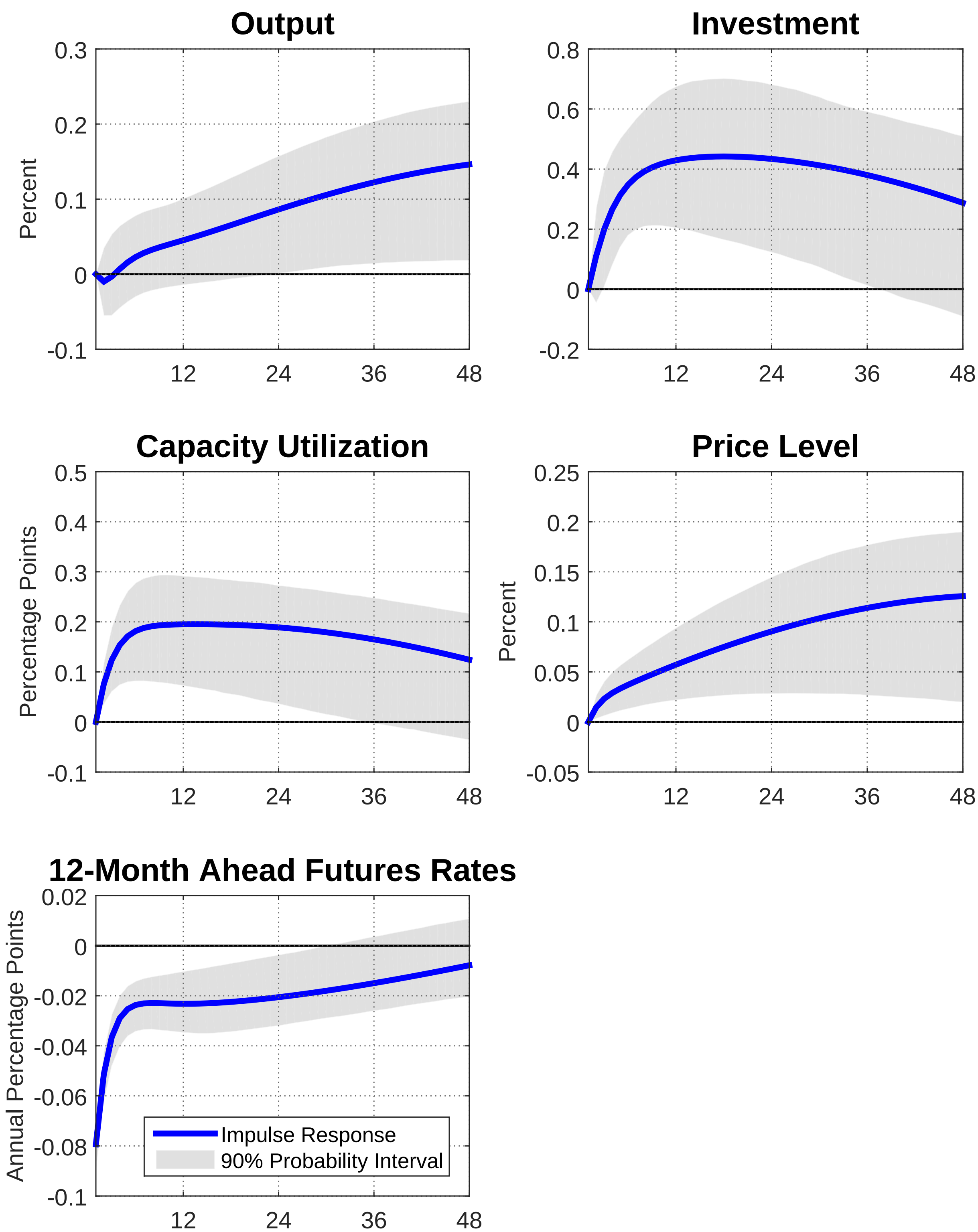
Note: The solid blue lines denote the empirical point estimate to a one standard deviation shock and the shaded areas denote the 90% probability interval of the posterior distribution.

Figure A.5: Empirical Impulse Responses with 2-Year Yield



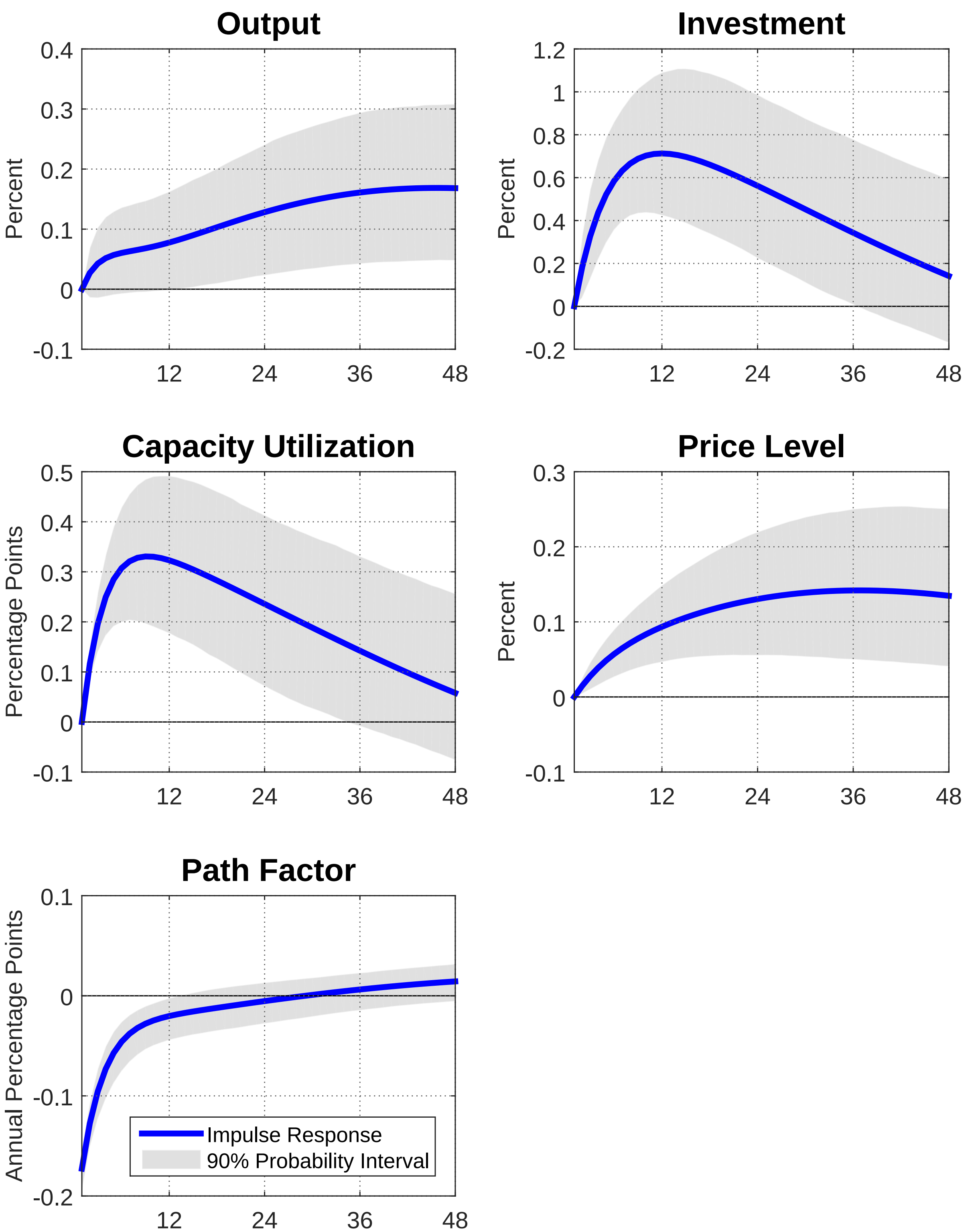
Note: The solid blue lines denote the empirical point estimate to a one standard deviation shock and the shaded areas denote the 90% probability interval of the posterior distribution.

Figure A.6: Empirical Impulse Responses with Recursive Identification



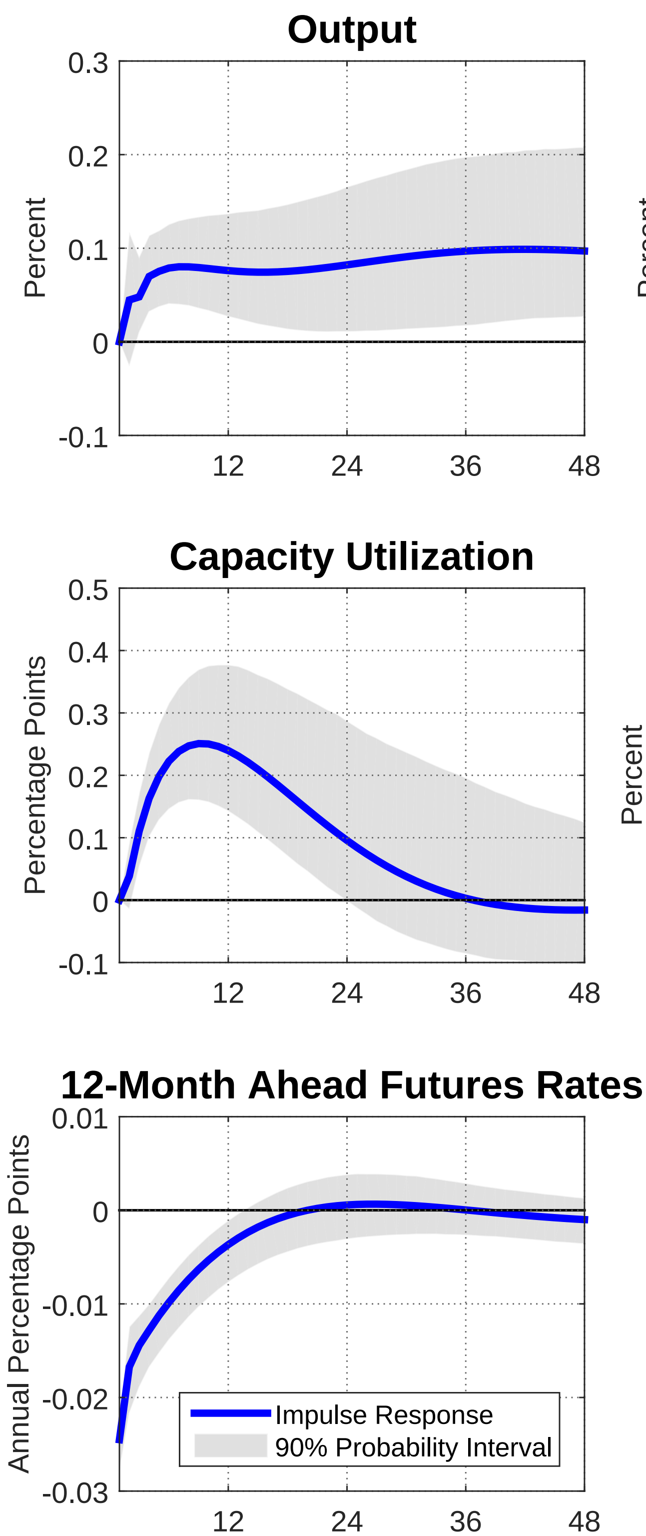
Note: The solid blue lines denote the empirical point estimate to a one standard deviation shock and the shaded areas denote the 90% probability interval of the posterior distribution.

Figure A.7: Empirical Impulse Responses During ZLB with Path Factor



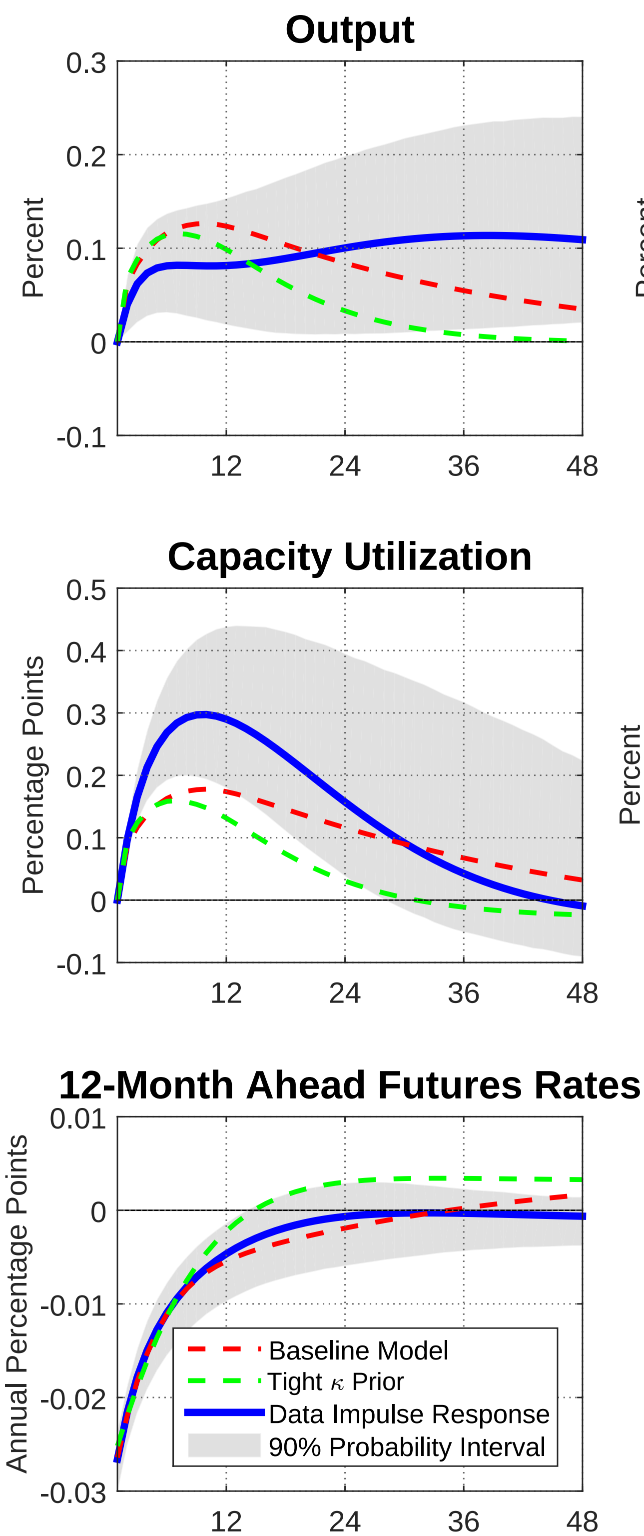
Note: The solid blue lines denote the empirical point estimate to a one standard deviation shock and the shaded areas denote the 90% probability interval of the posterior distribution.

Figure A.8: Empirical Impulse Responses with Additional Lags in the VAR



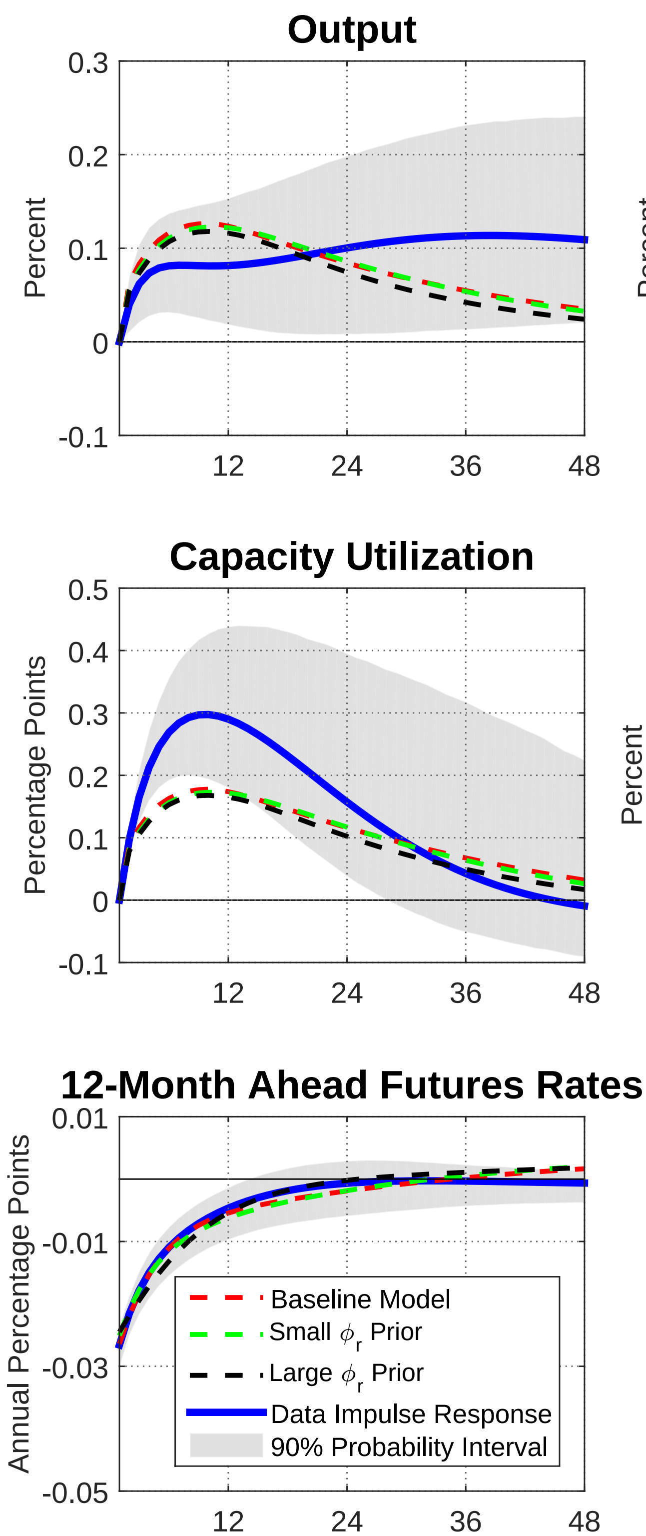
Note: The solid blue lines denote the empirical point estimate to a one standard deviation shock and the shaded areas denote the 90% probability interval of the posterior distribution.

Figure C.1: Empirical & Model Impulse Responses Under Tighter Prior for κ



Note: The solid blue lines denote the empirical point estimate to a one standard deviation shock and the shaded areas denote the 90% probability interval of the posterior distribution. The dashed lines denote a model-implied impulse response.

Figure C.2: Empirical & Model Impulse Responses Under Alternative Priors for ϕ_r



Note: The solid blue lines denote the empirical point estimate to a one standard deviation shock and the shaded areas denote the 90% probability interval of the posterior distribution. The dashed lines denote a model-implied impulse response.

Table C.1: Additional Impulse Response Matching Results

Baseline Estimates

Parameter	Description	Prior Distribution	Prior Mode	Prior Std. Dev.	Posterior Mode	Posterior Std. Dev.
b	Habit Persistence	Beta	0.50	0.25	0.7784	0.0210
ω	Calvo Probability	Beta	0.93	0.02	0.9535	0.0005
χ	Degree of Lagged Indexation	Beta	0.50	0.25	0.2735	0.0136
ϕ_r	Policy Rate Smoothing	Beta	0.75	0.25	0.7834	0.0073
κ	Investment Adjustment	Gamma	2.48	60.0	76.2051	4.8200
σ_δ	Capacity Utilization Curvature	Gamma	0.01	60.0	1.4811×10^{-5}	1.0727×10^{-4}
ρ_ν	Policy Shock Persistence	Beta	0.50	0.25	0.9545	0.0005
$1200 \times \sigma_\nu$	Std. Dev. of Policy Shock	Gamma	25.0	1200	0.0917	0.0038
$-\varepsilon_0^a \times \sigma_a$	Initial Aggregate Demand Shock	Uniform$(0, \infty)$			0.1506	0.0046

Tight Prior Over κ

Parameter	Description	Prior Distribution	Prior Mode	Prior Std. Dev.	Posterior Mode	Std. Dev.
b	Habit Persistence	Beta	0.50	0.25	0.7589	0.0662
ω	Calvo Probability	Beta	0.93	0.02	0.9294	0.0030
χ	Degree of Lagged Indexation	Beta	0.50	0.25	0.5009	0.0376
ϕ_r	Policy Rate Smoothing	Beta	0.75	0.25	0.9711	0.0008
κ	Investment Adjustment	Gamma	2.48	1.0	10.5208	1.0115
σ_δ	Capacity Utilization Curvature	Gamma	0.01	60.0	4.9715×10^{-4}	3.0237×10^{-4}
ρ_ν	Policy Shock Persistence	Beta	0.50	0.25	0.8234	0.0088
$1200 \times \sigma_\nu$	Std. Dev. of Policy Shock	Gamma	25.0	1200	0.0251	0.0010
$-\varepsilon_0^a \times \sigma_a$	Initial Aggregate Demand Shock	Uniform$(0, \infty)$			0.1882	0.0050

Small ϕ_r Prior

Parameter	Description	Prior Distribution	Prior Mode	Prior Std. Dev.	Posterior Mode	Std. Dev.
b	Habit Persistence	Beta	0.50	0.25	0.8035	0.0183
ω	Calvo Probability	Beta	0.93	0.02	0.9535	0.0005
χ	Degree of Lagged Indexation	Beta	0.50	0.25	0.3421	0.0091
ϕ_r	Policy Rate Smoothing	Beta	0.25	0.25	0.2464	0.0286
κ	Investment Adjustment	Gamma	2.48	60.0	65.2612	3.7727
σ_δ	Capacity Utilization Curvature	Gamma	0.01	60.0	1.0326×10^{-6}	3.0771×10^{-5}
ρ_ν	Policy Shock Persistence	Beta	0.50	0.25	0.9503	0.0005
$1200 \times \sigma_\nu$	Std. Dev. of Policy Shock	Gamma	25.0	1200	0.3639	0.0161
$-\varepsilon_0^a \times \sigma_a$	Initial Aggregate Demand Shock	Uniform$(0, \infty)$			0.1657	0.0044

Large ϕ_r Prior

Parameter	Description	Prior Distribution	Prior Mode	Prior Std. Dev.	Posterior Mode	Std. Dev.
b	Habit Persistence	Beta	0.50	0.25	0.8197	0.0060
ω	Calvo Probability	Beta	0.93	0.02	0.9603	0.0005
χ	Degree of Lagged Indexation	Beta	0.50	0.25	0.6274	0.0060
ϕ_r	Policy Rate Smoothing	Beta	0.95	0.25	0.9476	0.0011
κ	Investment Adjustment	Gamma	2.48	60.0	57.7179	4.7653
σ_δ	Capacity Utilization Curvature	Gamma	0.01	60.0	3.4317×10^{-5}	2.1389×10^{-5}
ρ_ν	Policy Shock Persistence	Beta	0.50	0.25	0.9445	0.0008
$1200 \times \sigma_\nu$	Std. Dev. of Policy Shock	Gamma	25.0	1200	0.0228	0.0009
$-\varepsilon_0^a \times \sigma_a$	Initial Aggregate Demand Shock	Uniform$(0, \infty)$			0.2049	0.0039