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## Working Paper A Replication of Anchored Inflation Expectations

I4R Discussion Paper Series, No. 174

**Provided in Cooperation with:** The Institute for Replication (I4R)

*Suggested Citation:* Blagov, Boris; Guljanov, Gaygysyz; Kharazi, Aicha (2024) : A Replication of Anchored Inflation Expectations, I4R Discussion Paper Series, No. 174, Institute for Replication (I4R), s.l.

This Version is available at: https://hdl.handle.net/10419/305222

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# **INSTITUTE** for **REPLICATION**

No. 174 I4R DISCUSSION PAPER SERIES

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October 2024



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I4R DP No. 174

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#### OCTOBER 2024

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## A Replication of Anchored Inflation Expectations\*

Boris Blagov, Gaygysyz Guljanov, Aicha Kharazi August 29, 2024

#### Abstract

Carvalho et al. (2023) propose a theoretical framework that explains longrun inflation expectations' dynamic using short-run inflation surprises and beliefs about monetary policy. In an empirical exercise, they show that this concise framework predicts long-term inflation expectations well over long periods and across a multitude of countries. In this study we look at the reproducibility of the work and the robustness of the results across two dimensions - the strength of the empirical results and the robustness of the estimation methodology. Across the empirical dimension, we extend the model with data past the global pandemic and study the robustness of the results before 2020 as well as the strength of the conclusion after 2020. With respect to the methodological application, we utilise a different sampler to estimate the main non-linear specification. The original findings remain intact across both dimensions.

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#### 1 Introduction

The paper "Anchored Inflation Expectations" by Carlos Carvalho, Stefano Eusepi, Emanuel Moench, and Bruce Preston analyses the long-run inflation expectations formation mechanism through the lens of a theoretical model that endogenises long-run expectations, making them a function of the agents' beliefs (firms' beliefs) regarding monetary policy and short-run inflation expectations. Thus, it provides a concise and tractable framework that explains inflation expectations' anchoring and de-anchoring using only a handful of variables. It is based on a New Keynesian model with imperfect information and bounded rationality, monopolistic competitive firms, and a central bank. There are two sources of uncertainty in this model: monetary policy and markup shocks. The agents in the model form a belief concerning the central bank target, which governs their expectation formation. As new data comes in each period, these beliefs are tested, and the agents decide whether the inflation target is constant or time-varying, hence providing a formal definition of inflation expectations anchoring.

Although it is conceptually challenging to detect episodes of unanchored expectations, this is one of the recent studies for estimating models with statedependent learning rules. Beliefs are updated over time using either a decreasinggain algorithm or a constant-gain algorithm. The authors generalise a Bayesian estimation methodology to test this theory empirically in a model with time variation in the degree of expectations anchoring. The empirical model is based on two key variables - inflation and short-term inflation forecasts - that are used to explain long-run inflation expectations.

The baseline results of the model are based on US data on the period 1970-2015, the full-span of data available at the time of writing. The main data sources for the empirical application are the standard inflation series and the Survey of Professional Forecasters, a source of inflation expectations. Due to the nature of surveys, expectations do not perfectly reflect expectations in the model. For

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example, professional forecasts do not cover all agents in the model and questions regarding future inflation relate to year-on-year changes in inflation rate. Further, model-implied expectations are often based on previous periods. The authors test the model's robustness and comparability using a variety of other measures, such as the Livingston Survey, Blue Chip Economic or Financial Forecasts, Consensus Forecasts, the Decision Makers Poll Survey, and the Michigan Survey of US Households. Additionally, the theory is applied to eight further countries - France, Germany, Italy, Spain, Canada, Japan, Sweden, and Switzerland. On the methodological side, the authors estimate several versions of the model in relation to how the agents update their beliefs about the inflation target.

Their analysis produces two key findings. First, the model appears to capture the evolution of long-run inflation expectations well and suggests poorly anchored inflation expectations before the great moderation from 1970 to 1990. Second, the stability of prices from the 2000s onwards is associated with anchored inflation expectations.

In this replication, prepared for the Institute for Replication (Brodeur et al. 2024), we attempt to reproduce the results in the paper using the codes provided by the authors and available on the journal webpage. We focus on the main conclusions for the US, which are based on publicly available data. We do not replicate the robustness checks in the original paper for the remaining countries as they utilise proprietary data. However, we report that our replication was successful and only minor issues were encountered along the way.

We then test their findings along two dimensions. First, we extend the data by more than eight years past the global pandemic. On the one hand, this allows us to examine whether a larger sample size influences the estimate and conclusions from the paper for the 1970-2015 period, and we find that the main results are robust to this extension. On the other hand, this replication sheds light on the recent debate on whether inflation expectations have been de-anchored following the global pandemic and the recent inflation surge. According to the model, there has been no-de-anchoring of long-run inflation expectations.

Second, we test the choice of methodology employed in the paper. The authors use a marginalised Kalman filter to estimate the non-linear specifications utilising Metropolis-Hastings (MH). In this replication, we check whether the MH is robust enough, as it can encounter issues when the posterior is badly behaved. This issue is a cause of concern given the heteroskedasticity inherent to macroeconomic data and potential non-linearities in the data associated with the long sample size, as the structure of the economy could have changed. As an alternative methodology, we use slice sampling (Planas et al. 2015, Neal 2003). We find that the results are robust to this change as well.

Our report is structured as follows. In Section 2, we briefly outline the model for completeness, report on the reproducibility of the results, and discuss minor issues encountered along the way. In Section 3, we present the empirical and methodological replications we carried out. Section 3 concludes.

#### 2 Reproducibility

#### 2.1 Baseline model with endogenous inflation drift

The framework of Carvalho et al. (2023) is a New Keynesian model with imperfect information, which is developed to understand how beliefs generate an endogenous inflation trend. This simple framework has a monopolistic competitive firm and a central bank. Firms set prices and face nominal rigidities, while a central bank has an inflation target. The formal model can be summed up with

#### the following equations:

$$\pi_{t} = (1 - \gamma)\Gamma\bar{\pi}_{t-1} + \gamma\pi_{t-1} + \phi_{t} + \mu_{t}$$
Aggregate supply curve  

$$\bar{\pi}_{t} = \bar{\pi}_{t-1} + k_{t-1}^{-1} \times f_{t-1}$$
Inflation target  

$$k_{t} = I(\bar{\pi}_{t-1}) \times (k_{t-1} + 1) + (1 - I(\bar{\pi}_{t-1})) \times \bar{g}^{-1}$$
Learning gain  

$$f_{t} = (1 - \gamma)(\Gamma - 1)\bar{\pi}_{t} + \mu_{t} + \epsilon_{t}$$
Monetary policy shock targeting  

$$\phi_{t} = \rho_{\phi}\phi_{t-1} + \epsilon_{t}$$
Monetary policy shock

To begin,  $\pi$  denotes the inflation  $\bar{\pi}$  is the inflation target, k is the learning gain, f represents the forecast error, and  $\phi$  is the monetary policy. Note that the markup shock is denoted by  $\mu$ , and the monetary policy shock is given by  $\epsilon$ . The key building blocks of the model are here the second and third equations, which describe how agents' beliefs regarding the evolution of inflation are formed. The agents (firms) "behave like econometricians" - they estimate current inflation (second equation) and update their estimate with the learning gain (third equation). In this case, the learning gain is either decreasing-(appropriate when the inflation target is stable) or constant (appropriate when there are shifts or drifts in inflation), with I representing an indicator function that depends on the observable forecast error between current and expected inflation.

The paper provides a formal discussion of how the model generates realistic responses to short and long-term expectations that are consistent with the observed data. For example, the specification of the learning gain and how the agents interact with their forecasting model gives rise to several versions of the model - a quasi-linear case and a full non-linear version, which we could replicate.

#### 2.2 Reproducing the paper using the provided code

The first point to make is that we were able to reproduce the results of the paper from the original code. There were, however, a couple of caveats to our reproduction that are worth mentioning.

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First and foremost, the majority of the robustness checks of the original paper include a variety of proprietary sources. For example, neither historical data from Consensus Economics, which is used for all non-US models, nor the Michigan survey data on long-term inflation expectations are available in the replication package. This omission is documented in the package, and the authors provide a data sheet where these data can be pasted (if available) for the code to run.

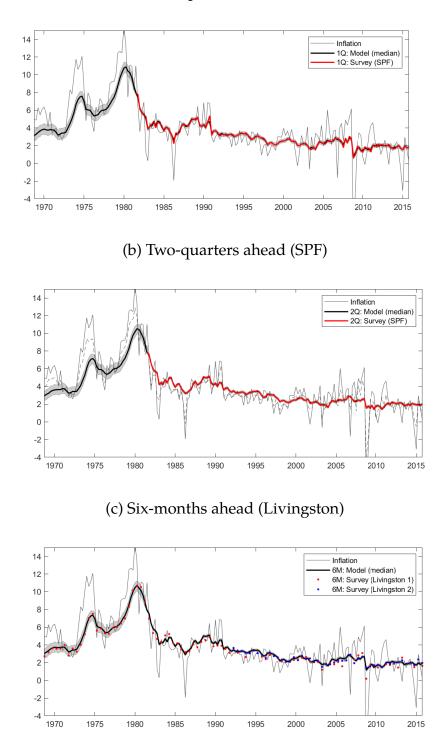
Second, there is a missing function at the beginning of the code. A setup function that lets the user decide the majority of options for the codes to run (i.e. which country or which survey datasets are to be used) but contains no estimation or data manipulation. This function is mentioned in the accompanying documentation; thanks to the error messages, when not run it is fairly straightforward to deduce which setup variables need to be defined. This minor issue was raised with the data editor, and we were supplied with the relevant function. However, by that time, we had also conducted the majority of the work on the replication. Consequently, we did not implement this function in our codes.

Third, some parameter definitions are hard coded. For example, the tightness of the MH-algorithm step (csquare in the code) for the US case of the linear model is set at  $c^2 = 0.5$ . It had to be lowered to  $c^2 = 0.003$  so that the algorithm could explore the parameter space. It is important to note that this procedure is also discussed in the paper in footnote 20. The authors had already implemented several lines with different values, and all we had to do was uncomment the relevant one. Such issues are nearly impossible to prevent in large codebases.

#### 2.3 Short-term expectations

Through the lens of the model, the authors demonstrate that the modelimplied short-term forecast closely matches the observations from Survey of Professional Forecasters, both one-quarter ahead and two-quarters ahead. The replication of the evolution of short-term inflation forecasts is illustrated in Figure 1, which corresponds to Figure 1 in the original manuscript. Notably, the

replication results are consistent with the findings in Carvalho et al. (2023). In Panels a and b, we report the model simulation of short-term inflation expectations using the Survey of Professional Forecasts data, which closely co-move with the CPI inflation. Panel c records the case of six-month-ahead inflation expectations. Looking at the entire pattern, the model-implied short-term expectations are shown to mimic the six-month-ahead average inflation forecasts from the Livingston Survey. Despite the resemblances in the movement of realised CPI inflation, the survey forecasts, and model-implied forecasts, we observe that the model becomes less volatile after the 1980s, as several survey observations fall outside the relative 95 percent credible intervals as in the original paper.



#### (a) One-quarter ahead (SPF)

Figure 1: Replication of short-term forecasts Carvalho et al. (2023)

<u>Notes</u>: The figure shows the model-implied short-term inflation forecasts and the analogues data from Livingston and SPF and the evolution of CPI inflation.

This analysis collectively signals out the changes in inflation expectations. A key contribution of the Carvalho et al. (2023) paper is to identify the changes in

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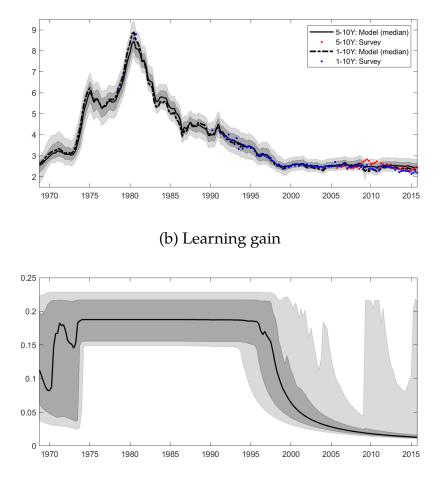
the sensitivity of long-run beliefs to new information. From Figure 1, we observe several breaks, the first one from the early 1970s to 1980, the second one from 1981 to 1987, and the third one from 1988 to 2005.

The years between 1970 and 1980, commonly known as the Great Inflation period, were marked by high level of inflation. This significant increase in inflation was most likely related to the surge in geopolitical uncertainty and the oil crisis in the 1970s. Carvalho et al. (2023) argue that this episode was characterised by the Fed's greater tolerance of inflation. The model-implied dynamics in shortterm inflation forecasts, across the three panels show a sharp spike from the 1970s until the 1980s, interrupted by an abrupt stabilisation period in 1976 and 1977. It is worth mentioning that while the model's short-term inflation forecasts closely track the CPI inflation, the model does not precisely generate the peak points seen in the data, in particular during the years when the inflation forecast underestimated the realised CPI inflation.

#### 2.4 Long-term Expectations

We now turn to the long-term inflation expectations. In their model, the authors compare the model-implied long-term inflation expectations against fiveto-ten-year-ahead average inflation forecasts and conclude that their patterns move in the same direction. We replicate their results and reach the same conclusion. Figure 2 illustrates the associated Figure 2 in the paper. It appears that the model-predicted five-to-ten-year-ahead forecast and one-to-ten-year-ahead forecast completely mirror the average inflation forecast from the corresponding surveys. Except for the years between 2008 and 2012, the reported inflation expectations from five-to-ten-year-ahead forecasts were higher than the model-induced forecasts but mostly situated within the 70 and 90 percent credible intervals. The fact that the model under-predicts the actual survey forecasts could be attributed to the severity of the 2008 global financial crisis, which shifted the long-term survey forecasts.

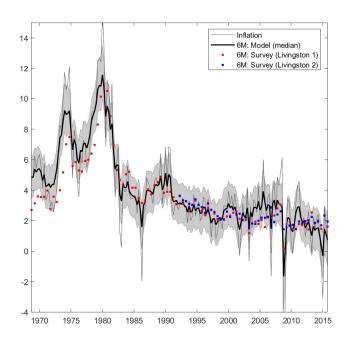
We also reproduce the model-implied learning gain over the period 1970-2015, and the results shown in Figure 2 panel b are consistent with the results in Carvalho et al. (2023). The authors highlight that the learning gain was mostly flat from 1975 to 1995. They interpret this as a persistent negative surprise during this period, which was characterised by disinflation. Notice that the 70 percent and 95 percent credible intervals are much wider in our replication than the one reported in the paper. Our replication also indicates high uncertainty in learning gain after the 2008 financial crisis.



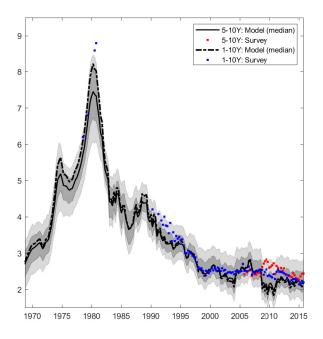
(a) Long term expectations

Figure 2: Replication of long-term forecasts Carvalho et al. (2023)

<u>Notes</u>: The figure shows the model-implied long-term inflation forecasts, its analogues data, and the model-predicted learning gain.



(a) Baseline model without long-term survey data



(b) Model with constant gain specification

#### Figure 3: Alternative models

<u>Notes</u>: Panel a shows the model-implied short-term inflation forecasts and analogues data, excluding long-term inflation expectations in the estimation. Panel b presents the model-induced long-term inflation expectations under the assumption that beliefs are updated using a constant-gain algorithm.

Fortunately, the structural model used in this analysis, although very simplified, assumes time variation in the sensitivity of agents' beliefs about inflation. The assumptions regarding what the learning gain captures are crucial to the interpretation of the results. Through the analysis of the simulated learning gain and inflation expectations, one can verify if the inflation expectations are anchored. As suggested by Carvalho et al. (2023), the weak link between inflation dynamics in the 2000s and economic shocks, and the stabilisation of expectations during this period indicates anchored inflation expectations. In contrast, the very nature of the 1970-1980 period caused an upsurge in inflation, and the dynamics in inflation after the 1980s indicate poorly anchored inflation expectations during that time. The authors recognise that variation in long-term expectations could originate in other policy-related factors rather than only short-term surprises.

#### 2.5 Additional specifications

The authors perform a variety of checks using (a) alternative gain specifications and (b) explicitly including/excluding long-term inflation expectation forecasts in the model. In contrast, the baseline model (results presented above) is estimated using short and long-term inflation expectations data from the Livingston Survey and the Survey of Professional Forecasters.

We perform these checks for several alternative gains, namely the baseline model without long-run survey data and the constant-gain specification. We include some of the results in Figure 3 instead of generating an identical Figure 6 to that in the original paper. Panel (a) of Figure 3 shows the model-implied short-term inflation forecasts, the CPI inflation, and the six-month-ahead inflation expectation from Livingston. In this counterfactual, we exclude the long-term inflation forecast survey data. Panel (b) of Figure 3 shows additional results under the assumption that beliefs are updated using a constant-gain algorithm. In this example, we report the model-predicted long-term inflation expectations and the corresponding survey data.

#### 3 Replication

In this section, we show the robustness replication along two dimensions. First, we look at the baseline results when extending the sample. Second, we consider a different sampler for estimating the model and compare the estimated parameters.

#### 3.1 Accounting for the global pandemic

We have conducted an additional replication exercise where we extend the data up to 2023 to sever two purposes. First, we can examine whether the findings prior to 2015 are robust to a longer dataset, adding more observations to estimate the model parameters. Second, we can test if the model results are robust when accounting for the global pandemic episode. In contrast to many other macroeconomic and financial series, the global pandemic and the subsequent lockdowns did not induce particularly strong outliers to inflation and inflation expectations - at least not as strong as the oil price shocks in the 1980s.

Nevertheless, the years following the recent global pandemic are characterised by inflationary pressure due to unprecedented government programmes and central bank interventions to mitigate the impact of the recession. They are also impacted by commodity price shocks following Russian aggression in Ukraine. Figure 4 records the one-quarter-ahead inflation expectations using the Survey of Professional Forecasts. The model-implied short-term forecasts keep pace with the survey forecasts and mimic slightly the surge in CPI inflation after 2020. The model captures the increase in inflation, although the actual increase was larger than the short-term forecasts. The shape of the increase is strikingly similar to the model fit during the first and second oil price shocks.

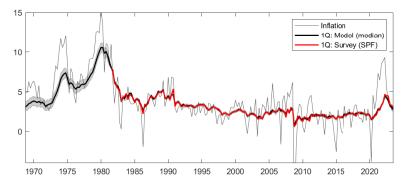
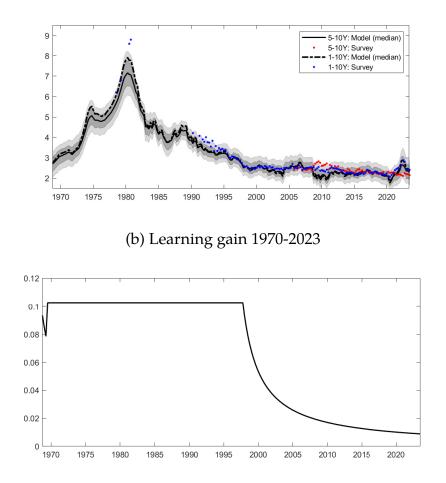


Figure 4: Short-term forecasts 1970-2023 model 2

<u>Notes</u>: The figure presents the model-predicted one-quarter ahead inflation expectations from the Survey of Professional Forecasts including the pandemic crisis period



(a) Long term expectations 1970-2023

Figure 5: Replication of long-term forecasts 1970-2023 Carvalho et al. (2023)

<u>Notes</u>: The figure shows the model-implied long-term expectation, its corresponding data, and the model-implied learning gain including the pandemic crisis period.

We report in Figure 5 the model-implied long-run inflation expectations and

survey inflation forecasts (Panel (a)) along with the median of the learning gain (Panel (b)). In general, the results remain consistent with Carvalho et al. (2023) when we include the global pandemic crisis. Long-term expectations closely match the observations from the survey. More importantly, one can see that model-predicted long-run inflation expectations increase after 2020. We also observe differences between the survey-based measure of long-term expectations versus the model predictions. In particular, the five-to-ten-year-ahead inflation survey forecasts are lower than the ones predicted by the model. Interestingly, we find no evidence of de-anchoring, as indicated by the learning gain.

#### 3.2 Methodological considerations

Next, we consider some methodological aspects of the paper, namely the estimation method. The model's parameters are estimated using the (random walk) MH algorithm and the marginalised particle filter. The MH algorithm is an industry standard. However, it may encounter problems if the shape of the posterior distribution is irregular (Herbst and Schorfheide 2016, page 65). Furthermore, the MH algorithm needs careful specification of the proposal variance. A common approach is to set it to the negative inverse Hessian at the posterior mode.

Unfortunately, in many applications the maximisation of the posterior density is tedious and the numerical approximation of the Hessian may be inaccurate. These problems may arise if the posterior distribution is very non-elliptical and possibly multimodal, or if the likelihood function is replaced by a nondifferentiable particle filter approximation (Herbst and Schorfheide 2016, page 68).

	MH sampler				Slice sampler			
	Mode	Mean	5%	95%	Mode	Mean	5%	95%
$\pi^*$	2.46	2.47	2.10	2.88	2.46	2.48	2.10	2.89
$\bar{ heta}$	0.02	0.03	0.01	0.05	0.02	0.03	0.01	0.05
Ī	0.12	0.14	0.10	0.20	0.15	0.15	0.10	0.20
γ	0.12	0.13	0.09	0.17	0.13	0.13	0.09	0.17
Г	0.93	0.89	0.81	0.95	0.94	0.89	0.81	0.95
ρ	0.87	0.88	0.83	0.92	0.86	0.87	0.82	0.92
$\sigma_{ ilde{\epsilon}}$	0.09	0.08	0.07	0.10	0.08	0.09	0.07	0.10
$\sigma_{ ilde{\mu}}$	0.37	0.36	0.30	0.42	0.37	0.36	0.31	0.42
$\sigma_{o,1}$	0.26	0.28	0.22	0.34	0.26	0.28	0.21	0.34
$\sigma_{o,2}$	0.04	0.04	0.04	0.05	0.04	0.05	0.04	0.05
σ <sub>0,3</sub>	0.02	0.02	0.01	0.03	0.03	0.03	0.01	0.03
$\sigma_{o,4}$	0.07	0.07	0.06	0.08	0.08	0.08	0.06	0.08
$\sigma_{o,5}$	0.05	0.05	0.04	0.06	0.05	0.05	0.04	0.06

Table 1: Marginal posterior distributions of the model parameters.

<u>Notes</u>: This table shows the estimation results using the MH sampler (left side of the table), the slice sampler (right side of the table) as in Planas et al. (2015).  $\pi^*$  value has been multiplied by 4 for comparison purposes with the original manuscript where it is annualized.

An alternative sampling scheme that can prove useful in particular non-linear cases is slice sampling (Planas et al. 2015, Neal 2003), which uses an auxiliary variable rather than a proposal distribution. This method requires sampling from the joint distribution of the auxiliary and the main variables in the Gibbs sampling fashion. To obtain the marginal distribution of the main variables, the samples from the auxiliary variables are ignored. The slice sampler does not need to specify the posterior covariance matrix, but it can be improved substantially if available. For this application, we use the original dataset until 2015 but do not use the authors' code for the sampling; instead we implement our own. As reported in Table 1, we find that implementing this robustness check has no considerable effect on the estimates. The paper reports the annualised value for

 $\pi^*$ , which is standard with US data; the estimated parameters on the first line have been multiplied by four.

#### 4 Conclusion

Overall, we conclude that the results of Carvalho et al. (2023) are reproducible for the non-proprietary data case (which are also their baseline results). They are also robust to extending the data even after the global pandemic, where many other methodologies would fail to using a different sampler to deal with the inherent non-linearities of the theoretical framework.

#### References

- Brodeur, A., Mikola, D., Cook, N. and coauthors: 2024, Mass reproducibility and replicability: A new hope, *I4R Discussion Paper 107*. URL: https://hdl.handle.net/10419/289437
- Carvalho, C., Eusepi, S., Moench, E. and Preston, B.: 2023, Anchored inflation expectations, *American Economic Journal: Macroeconomics* 15(1), 1–47. URL: https://www.aeaweb.org/articles?id=10.1257/mac.20200080
- Herbst, E. and Schorfheide, F.: 2016, *Bayesian Estimation of DSGE Models*, The Econometric and Tinbergen Institutes Lectures, Princeton University Press.
- Neal, R. M.: 2003, Slice sampling, *The Annals of Statistics* **31**(3), 705 767. **URL:** *https://doi.org/10.1214/aos/1056562461*
- Planas, C., Ratto, M. and Rossi, A.: 2015, Slice sampling in bayesian estimation of dsge models, *Conference paper presented at 11th DYNARE conference*.