Online Appendix to
"The Term Structure of Inflation Expectations"

Mikhail Chernov[a,b], Philippe Mueller[a,*]

[a] *London School of Economics, London, UK*
[b] *CEPR*

Abstract

Appendix A summarizes the procedure used for projecting unobservable factors onto macro factors. Appendix B provides a simple model of heterogenous agents that is consistent with our reduced-from model. Appendix C describes the objective function for the likelihood estimation. Appendix D clarifies the role of survey data in estimating the model parameters. Appendix E contains tables with the parameter estimates including bootstrapped confidence intervals for eight of the models.

Appendix A. Projection

The model that controls the evolution of state z can be written as

$$z_t = \mu_z + \Phi_z z_{t-1} + \Sigma_z^{1/2}\epsilon_t \tag{A.1}$$

$$= \begin{bmatrix} \mu^x \\ \mu^m \end{bmatrix} + \begin{bmatrix} \Phi^{xx} & \Phi^{xm} \\ \Phi^{mx} & \Phi^{mm} \end{bmatrix} \begin{bmatrix} x_{t-1} \\ m_{t-1} \end{bmatrix} + \begin{bmatrix} \Sigma^{xx} & \Sigma^{xm} \\ \Sigma^{mx} & \Sigma^{mm} \end{bmatrix} \begin{bmatrix} \epsilon_t^x \\ \epsilon_t^m \end{bmatrix}. \tag{A.2}$$

Liptser (1997) and Liptser and Shiryaev (2001) derive the projection of one element of the VAR(1) on the other using the same ideas as in the Kalman filtering. In particular, these authors provide the following expression for the conditional mean, often referred to as "forecast," and variance of the forecast error:

$$\begin{aligned} \hat{x}(m^t) &= \mu^x + \Phi^{xx}\hat{x}(m^{t-1}) + \Phi^{xm}m_{t-1} \\ &+ \left(\Sigma^{xx}\Sigma^{mx\prime} + \Sigma^{xm}\Sigma^{mm\prime} + \Phi^{xx}P_{t-1}\Phi^{mx\prime}\right)\left(\Sigma^{mx}\Sigma^{mx\prime} + \Sigma^{mm}\Sigma^{mm\prime} + \Phi^{mx}P_{t-1}\Phi^{mx\prime}\right)^{-1} \\ &\times \left(m_t - \mu_m - \Phi^{mx}\hat{x}(m^{t-1}) - \Phi^{mm}m_{t-1}\right) \end{aligned} \tag{A.3}$$

*Corresponding author: London School School of Economics, Department of Finance, Houghton Street, London WC2A 2AE, Phone: +44 20 7955 7012.

Email addresses: m.chernov@lse.ac.uk (Mikhail Chernov), p.mueller@lse.ac.uk (Philippe Mueller)

$$
\begin{aligned}
P_t &= \Phi^{xx} P_{t-1} \Phi^{xx\prime} + (\Sigma^{xx}\Sigma^{xx\prime} + \Sigma^{xm}\Sigma^{xm\prime}) \\
&- (\Sigma^{xx}\Sigma^{mx\prime} + \Sigma^{xm}\Sigma^{mm\prime} + \Phi^{xx} P_{t-1} \Phi^{mx\prime}) (\Sigma^{mx}\Sigma^{mx\prime} + \Sigma^{mm}\Sigma^{mm\prime} + \Phi^{mx} P_{t-1} \Phi^{mx\prime})^{-1} \\
&\times (\Sigma^{xx}\Sigma^{mx\prime} + \Sigma^{xm}\Sigma^{mm\prime} + \Phi^{xx} P_{t-1} \Phi^{mx\prime})', \qquad \text{(A.4)}
\end{aligned}
$$

where we generically refer to m and x as vectors of observable and latent variables, respectively.

We introduce additional notations to describe the projection initialization. The long-run mean and variance of z are:

$$
(I - \Phi)^{-1} \mu = \begin{bmatrix} \Theta^m \\ \Theta^x \end{bmatrix} \qquad \text{(A.5)}
$$

$$
V = \begin{bmatrix} V^{xx} & V^{xm} \\ V^{mx} & V^{mm} \end{bmatrix}, \text{ where } V \text{ solves } V = \Phi V \Phi' + \Sigma\Sigma' \qquad \text{(A.6)}
$$

The steady-state matrix P satisfies:

$$
\begin{aligned}
P &= \Phi^{xx} P \Phi^{xx\prime} + (\Sigma^{xx}\Sigma^{xx\prime} + \Sigma^{xm}\Sigma^{xm\prime}) \\
&- (\Sigma^{xx}\Sigma^{mx\prime} + \Sigma^{xm}\Sigma^{mm\prime} + \Phi^{xx} P \Phi^{mx\prime}) (\Sigma^{mx}\Sigma^{mx\prime} + \Sigma^{mm}\Sigma^{mm\prime} + \Phi^{mx} P \Phi^{mx\prime})^{-1} \\
&\times (\Sigma^{xx}\Sigma^{mx\prime} + \Sigma^{xm}\Sigma^{mm\prime} + \Phi^{xx} P \Phi^{mx\prime})' \qquad \text{(A.7)}
\end{aligned}
$$

Then the projection is initialized as follows:

$$
\hat{x}(m_0) = \Theta^x + V^{xm}(V^{mm})^{-1}(m_0 - \Theta^m), \; P_0 = P \qquad \text{(A.8)}
$$

In this case $P_t = P$ and the projection is time-stationary. An alternative strategy is to initialize P_0 at the unconditional variance of z. In this case, the sequence P_t will converge to P. In our model it happens in twelve steps.

The lags of the projected x in expression (A.3) could be recursively substituted out so that the current projection is expressed as a distributed-lag function of macro variables:

$$
\hat{x}(m^t) = c(\psi) + \sum_{j=0}^{t} c_{t-j}(\psi) m_{t-j}, \qquad \text{(A.9)}
$$

where the matrices c are functions of parameters ψ that control the dynamics of the state variables z.

Appendix B. A model of learning with heterogeneous beliefs

We start out by describing the evolution of changes in CPI π_t in the most basic form:

$$
\pi_t = e_{t-1} + \sigma \epsilon_t^{\pi} \qquad \text{(B.1)}
$$

where e_t represents expected inflation rate. We fill this equation with more content by assuming that e_t is determined by π_t and some state variable s_t that is unobservable to the agents. We further assume that the vector $u_t = (\pi_t, s_t)'$ follows a VAR(1) process

$$
\begin{aligned}
u_t &= \mu^u + \Phi^u u_{t-1} + \Sigma^u \epsilon_t^u && \text{(B.2)}\\
&= \begin{bmatrix} \mu^\pi \\ \mu^s \end{bmatrix} + \begin{bmatrix} \phi^{\pi\pi} & \phi^{\pi s} \\ \phi^{s\pi} & \phi^{ss} \end{bmatrix} \begin{bmatrix} \pi_{t-1} \\ s_{t-1} \end{bmatrix} + \begin{bmatrix} \sigma^{\pi\pi} & 0 \\ \sigma^{s\pi} & \sigma^{ss} \end{bmatrix} \begin{bmatrix} \epsilon_t^\pi \\ \epsilon_t^s \end{bmatrix}. && \text{(B.3)}
\end{aligned}
$$

In particular, this specification implies that the spot expectation of CPI changes is:

$$e_t = E_t(\pi_{t+1}) = \mu^\pi + \phi^{\pi\pi}\pi_t + \phi^{\pi s} s_t. \tag{B.4}$$

Since s_t is not observable the agents must filter it. We use a setup that is similar to the one in Scheinkman and Xiong (2003), who develop stock pricing in the context of investors with heterogeneous beliefs. For transparency, we assume that there are only two forecast surveys being conducted: A and B. Participants of the surveys receive signals θ_t^A and θ_t^B about s_t. Members of survey A think of the signal θ^A as their own, but can observe both. Specifically, forecaster A believes that only her signal is correlated with innovations in s_t, i.e., the vector $w_t = (\pi_t, \theta_t^A, \theta_t^B, s_t)'$ follows a restricted VAR(1) process:[1]

$$
\begin{aligned}
w_t &= \mu^w + \Phi^w w_{t-1} + \Sigma^w \epsilon_t^w && \text{(B.5)}\\
&= \begin{bmatrix} \mu^\pi \\ 0 \\ 0 \\ \mu^s \end{bmatrix} + \begin{bmatrix} \phi^{\pi\pi} & 0 & 0 & \phi^{\pi s} \\ 0 & 1 & 0 & 1 \\ 0 & 0 & 1 & 1 \\ \phi^{s\pi} & 0 & 0 & \phi^{ss} \end{bmatrix} \begin{bmatrix} \pi_{t-1} \\ \theta_{t-1}^A \\ \theta_{t-1}^B \\ s_{t-1} \end{bmatrix} + \begin{bmatrix} \sigma^{\pi\pi} & 0 & 0 & 0 \\ -\frac{\sigma^{s\pi}\sigma^{s\theta^A}}{\sigma^{\theta^A\theta^A}} & \sigma^{\theta^A\theta^A} & 0 & 0 \\ 0 & 0 & \sigma^{\theta^B\theta^B} & 0 \\ \sigma^{s\pi} & \sigma^{s\theta^A} & 0 & \sigma^{ss} \end{bmatrix} \begin{bmatrix} \epsilon_t^\pi \\ \epsilon_t^{\theta^A} \\ \epsilon_t^{\theta^B} \\ \epsilon_t^s \end{bmatrix},
\end{aligned}
$$

where $\epsilon_t \sim N(0, I)$. The restrictions ensure that the private signal is not correlated with π_t, and that the expected change in the private signal is equal to the unobserved state variable. The element $\sigma^{s\theta^A}$ controls the degree of informativeness of the signal regarding the state variable s.

We solve the forecaster's filtering problem using the results from appendix Appendix A, expression (A.9), in particular. In our Gaussian setup the filtered value of the state variable s will be a linear function of π, the private signals

[1]A symmetric argument applies to the members of survey B.

and their lags:

$$\hat{s}^i_t = c^i_0 + \sum_{j=0}^{t} \left(c^i_{\pi,t-j}\pi_{t-j} + c^i_{\theta,t-j}\theta^i_{t-j} + c^{-i}_{\theta,t-j}\theta^{-i}_{t-j} \right), \tag{B.6}$$

where i and $-i$ generically refer to one of the surveys, and all others, respectively. Therefore, expected change in CPI from the survey i is equal to:

$$e^i_t = E^i_t(\pi_{t+1}) = \mu^\pi + \phi^{\pi\pi}\pi_t + \phi^{\pi s}\hat{s}^i_t. \tag{B.7}$$

As a next step, we adopt this result in our empirical setting. An econometrician does not observe the private signals θ^i, therefore she has to estimate them, which would require adding a second layer of filtering equations. We want to avoid this complication and introduce additional notations and some approximations.

Firstly, we assume that first p lags of the variables are sufficient to approximate $\hat{s}^i$ in (B.6) accurately. We stack up the contemporaneous and lagged values of the variables in (B.6) into a vector: $\varsigma^p_t = (\pi_{t-1}, \ldots, \pi_{t-p}, \theta^i_t, \ldots, \theta^i_{t-p}, \theta^{-i}_t, \ldots, \theta^{-i}_{t-p})'$. Now we can rewrite $\hat{s}^i$ as

$$\hat{s}^i_t \approx c^i_0 + c^i_{\pi,t}\pi_t + c^{i\prime}\varsigma^p_t \tag{B.8}$$

Secondly, we assume that a vector x_t of first k principal components of ς^p_t explains most of the variation in this variable. Therefore,

$$\hat{s}^i_t \approx c^i_0 + c^i_{\pi,t}\pi_t + \alpha^{i\prime}x_t \tag{B.9}$$

where α^i is a convolution of c^i and the principal components loadings on ς^p_t. In particular, these assumptions combined with the CPI forecast equation (B.4) implies that, regardless of the survey, forecasts of CPI changes will be linear functions of π_t and x_t, but that the weights in these functions will be survey-specific:

$$e^i_t = E^i_t(\pi_{t+1}) = \nu^i_0 + \nu^i_\pi\pi_t + \nu^i_x x_t, \tag{B.10}$$

Note that,because the vector $(\pi_t, \varsigma^{p\prime}_t)'$ follows a VAR(1), the vector $(\pi_t, x'_t)'$ will do so as well. This observation yields our reduced-form setup.[2]

[2] In practice the accuracy of the approximation can be achieved by using a sufficient number of the latent factors x_t. The sufficiency can be established via model specification analysis.

Appendix C. Estimation

We estimate our models via maximum likelihood with the Kalman filter. The models we estimate differ along three dimensions: (a) the number of factors $N+1$, (b) the observable data used in the estimation and (c) the restrictions imposed at the estimation stage. The AST and AOT models use all available data in the estimation but impose different restrictions with regards to the inflation forecasts. All other models use a subset of the data.

The stacked parameters that control the dynamics of the state variables ($\mathbb{P}$-parameters) are denoted by ψ. Parameters $\psi^{\mathbb{Q}}$ and $\psi^{\mathbb{P}^i}$ control the dynamics (drifts) under the risk neutral measure $\mathbb{Q}$ and the subjective probability measure $\mathbb{P}^i$, respectively. We denote the full set of model parameters by $\Theta = (\psi', \psi^{\mathbb{Q}\prime}, \psi^{\mathbb{P}^i\prime})'$.

We collect the observable data at time t in the vector $\mathbf{y}_t$. The observables may include the macro variables g and π, Treasury and TIPS yields and the various inflation survey forecasts, that is, $\mathbf{y}_t = (g, \pi, Treas_t', TIPS_t', Surv_t^{i\prime})'$. Let $\mathbf{w}_t$ be the vector of measurement errors, including ω_t^n, ω_t^r and χ_t^i. The first two elements of $\mathbf{w}_t$ are zero as we assume that the macro variables are observed without error. The vector $\mathbf{y}^t$ summarizes all the observed data through date t, $\mathbf{y}^t \equiv (\mathbf{y}_t', \mathbf{y}_{t-1}', \ldots, \mathbf{y}_1')'$.

Given the model setup and implications derived in the main text, we have

$$\mathbf{y}_t | \mathbf{y}^{t-1}; \Theta \sim \mathcal{N}\left(\mathbf{v}_t(\Theta), \mathbf{F}_t(\Theta)\right), \tag{C.1}$$

where

$$\mathbf{v}_t(\Theta) = \mathbf{A}(\Theta) + \mathbf{B}(\Theta)' z_{t|t-1}(\Theta), \tag{C.2}$$

$$\mathbf{F}_t(\Theta) = \mathbf{B}(\Theta)' P_{t|t-1}(\Theta) \mathbf{B}(\Theta) + I_k \mathbf{w}_t, \tag{C.3}$$

where $\mathbf{v}_t(\Theta)$ denotes the optimal forecast conditional on having observed the full data history up to $t-1$ and $\mathbf{F}_t(\Theta)$ is the mean squared error of the forecast; $z_{t|t-1}(\Theta)$ is the conditional mean of the state variables and $P_{t|t-1}(\Theta)$ the conditional covariance matrix obtained via the standard Kalman filter recursion. The Kalman filter iteration is started with the unconditional variance $P_{1|0}(\Theta) = \left(\mathbf{I}_{(N+1)^2} - (\Phi_z \otimes \Phi_z)\right)^{-1} \cdot \mathrm{vec}(\Sigma_z)$. In total, we have k observed variables at date t and I_k is the identity matrix of size k. $\mathbf{A}(\Theta)$ is a $k \times 1$ vector and $\mathbf{B}(\Theta)$ is a $(N+1) \times k$ matrix of factor loadings for the observables.

The resulting likelihood function is:

$$\mathcal{L} = -\frac{kT}{2} \log(2\pi) - \frac{1}{2} \sum_{t=1}^{T} \log |\mathbf{F}_t(\Theta)| - \frac{1}{2} \sum_{t=1}^{T} [\mathbf{y}_t - \mathbf{v}_t(\Theta)]' \, \mathbf{F}_t^{-1}(\Theta) \, [\mathbf{y}_t - \mathbf{v}_t(\Theta)] \,. \tag{C.4}$$

We can deal with any set of observable data during estimation by using different vectors of data $\mathbf{y}_t$ and specifying different conditional forecasts and conditional variance-covariance matrix. For AST and AOT, $\mathbf{y}_t$ is the full vector described above; for AS and AO, the vector excludes $TIPS_t$; for NFT it excludes $Surv_t^i$. For the NF model we have $\mathbf{y}_t = (g, \pi, Treas_t')'$ and for the OF and OFO models we have $\mathbf{y}_t = (g, \pi, Surv_t^{i\prime})'$. Furthermore, it is straightforward to deal with missing values in the estimation by simply excluding the missing quantity from $\mathbf{y}_t$ for iteration t. This likelihood is augmented by a penalty that controls the size of risk premia as described in the main text.

The parameter restrictions also have a direct effect on the objective function at the estimation stage. For the AST and AS models, no restrictions are imposed on the parameter vector Θ. Therefore, Θ^{AS} or $\Theta^{\text{AST}} = (\psi', \psi^{\mathbb{Q}\prime}, \psi^{\mathbb{P}^i\prime})'$. The AOT and AO models do not allow for expectation disagreements and hence Θ^{AO} or $\Theta^{\text{AOT}} = (\psi', \psi^{\mathbb{Q}\prime})'$. In the NF and NFT models, surveys are not included and hence we again have Θ^{NF} or $\Theta^{\text{NFT}} = (\psi', \psi^{\mathbb{Q}\prime})'$. The OF model does not include any yields, hence $\Theta^{\text{OF}} = (\psi', \psi^{\mathbb{P}^i\prime})'$. Finally, the OFO model neither contains yields nor does it allow for term expectation disagreements and hence $\Theta^{\text{OFO}} = \psi'$.

Appendix D. The impact of survey data on estimation

As we pointed out in the main text, if there are no hidden factors, using survey forecasts in estimation cannot have a material effect on inflation forecasts if model-based subjective expectations are allowed to diverge from model-based objective expectations in an arbitrary fashion. We provide details of this reasoning in this section.[3]

We discuss the case of the AS model to be specific. We specialize the equations from section Appendix C as follows. Split the vector $\mathbf{y}_t$ into $\mathbf{y}_{1t}$ that contains g, π, and $N-1$ nominal yields, $\mathbf{y}_{2t}$ that contains the remainder of yields, and $\mathbf{y}_{3t} = Surv_t^{i\prime}$ (the allocation of g and π to $\mathbf{y}_{1t}$ is without loss of generality). Vectors of measurement errors $\mathbf{w}_{jt}$ are the corresponding splits of the overall vector $\mathbf{w}_t$. To make the argument clear, we further assume that $\mathbf{w}_{1t} = 0$ and, therefore, Kalman filtering is not needed as state variables can be inverted from the observables $\mathbf{y}_{1t}$. Importantly, this implication is correct only if there are no hidden factors. Otherwise, it is impossible to infer the entire state from macro variables and yields only. Please refer to the main text for the detailed discussion of this point.

As a result, the optimal forecast $\mathbf{v}_t(\Theta)$ can be represented as:

$$\mathbf{v}_{1t}(\Theta) \quad = \quad \mathbf{A}_1(\psi, \psi^{\mathbb{Q}}) + \mathbf{B}_1(\psi, \psi^{\mathbb{Q}})' z_t(\mathbf{y}_{1t}, \psi, \psi^{\mathbb{Q}}) = \mathbf{y}_{1t}, \tag{D.1}$$

[3] We are grateful to the Referee for showing us the derivations related to this point.

$$\mathbf{v}_{2t}(\Theta) = \mathbf{A}_2(\psi, \psi^{\mathbb{Q}}) + \mathbf{B}_2(\psi, \psi^{\mathbb{Q}})' z_t(\mathbf{y}_{1t}, \psi, \psi^{\mathbb{Q}})$$

$$= \mathbf{A}_2(\psi, \psi^{\mathbb{Q}}) + \mathbf{B}_2(\psi, \psi^{\mathbb{Q}})'(\mathbf{B}_1(\psi, \psi^{\mathbb{Q}})')^{-1}(\mathbf{y}_{1t} - \mathbf{A}_1(\psi, \psi^{\mathbb{Q}})), \tag{D.2}$$

$$\mathbf{v}_{3t}(\Theta) = \mathbf{A}_3(\psi^{\mathbb{P}^i}) + \mathbf{B}_3(\psi^{\mathbb{P}^i})' z_t(\mathbf{y}_{1t}, \psi, \psi^{\mathbb{Q}})$$

$$= \mathbf{A}_3(\psi^{\mathbb{P}^i}) + \mathbf{B}_3(\psi^{\mathbb{P}^i})'(\mathbf{B}_1(\psi, \psi^{\mathbb{Q}})')^{-1}(\mathbf{y}_{1t} - \mathbf{A}_1(\psi, \psi^{\mathbb{Q}})). \tag{D.3}$$

If model-based subjective expectations are allowed to diverge from model-based objective expectations in an arbitrary fashion, then for any arbitrary vector a and arbitrary matrix b, there exist parameter vector $\tilde{\psi}^{\mathbb{P}^i}$ such that $\mathbf{A}_3(\tilde{\psi}^{\mathbb{P}^i}) = a$ and $\mathbf{B}_3(\tilde{\psi}^{\mathbb{P}^i}) = b$. This means that for each set of parameters $(\psi, \psi^{\mathbb{Q}})$, one can find a set of parameters $\psi^{\mathbb{P}^i}$, such that the forecast $\mathbf{v}_{3t}(\Theta)$ is the same. Therefore,

$$\mathbf{v}_{3t}(\Theta) = \mathbf{A}_3^* + \mathbf{B}_3^* \mathbf{y}_{1t} = \mathbf{v}_{3t}(\mathbf{A}_3^*, \mathbf{B}_3^*), \tag{D.4}$$

where $\mathbf{A}_3^*$ and $\mathbf{B}_3^*$ are free parameters that do not depend on Θ. Thus, the inclusion of the survey data in the estimation has no impact on parameters $(\psi, \psi^{\mathbb{Q}})$ if $\psi^{\mathbb{P}^i}$ is allowed to be different from ψ and there are no hidden variables. When $\mathbf{w}_{1t}$ is as in our original setup, Kalman filtering is required and survey data are helpful in estimating the state $z_{t|t-1}$ and parameters ψ that control the dynamics of the state. The marginal effect could be small, however.

Appendix E. Parameter estimates

We have estimated a total of 16 models (four- and five-factor versions of eight kinds of models, depending on which data were used in the estimation). In the following, we report the parameter estimates and bootstrapped confidence 95% intervals for NF4, NFT4, AO5, AOT5, AS5, AST5, OF4 and OFO4.

Prior to estimation, the data were rescaled by dividing all the rates by 400, so that the numbers corresponded to quarterly rates observed at quarterly frequency and were expressed in decimals. The reported parameter estimates reflect this scaling. This convention is convenient because it is difficult to determine the implications of the models, especially the ones that pertain to second moments, if percentages or annualized rates observed at quarterly frequencies are used. In the main text of the paper, all the results are reported in terms of annualized percentages because this is more straightforward pedagogically.

Finally, the reported parameter values correspond to the final model rotation. We rotate the model so that the residual factors f are orthogonal to each other, and so that x_1 is interpreted as the factor that is driving the level of the nominal yield curve, and, in the case of a five factor model, x_2 is interpreted as the factor that is driving the slope, measured as the difference between the 10-year and three-month yields, of the nominal yield curve. This specific rotation is, of course, irrelevant for some of our results (such as pricing errors and forecasting). However, we use it to interpret the model's implications, such as factor loadings. Moreover, we have to pick a rotation in order to calculate the confidence intervals of the parameters. Because of our choice of rotation, a reader will see a lot of non-zero elements in matrices where one would expect zeros on the basis of our discussion of identification in the main text.

References

Liptser, R. S., 1997. Stochastic control, lecture Notes, Tel Aviv University.

Liptser, R. S., Shiryaev, A. N., 2001. Statistics of Random Processes: I. General Theory, 2nd Edition. Springer, Berlin Heidelberg.

Scheinkman, J., Xiong, W., 2003. Overconfidence and speculative bubbles. Journal of Political Economy 111, 1183–1219.

Table 1: Parameters NF4

Real interest rate					
	$\delta_{x,0}$	δ_x			
		x_1	x_2		
	0.003	0.003	-0.0003		
	[-0.001, 0.006]	[0.002,0.004]	[-0.001,0.001]		
Real risk premia					
	Λ_0	Λ_1			
		x_1	x_2	g	
x_1	0.11	-0.01	0.24	-30.75	
	[-0.09, 0.42]	[-0.16,0.17]	[-0.03,0.58]	[-68.96,-3.80]	
x_2	0.64	0.39	0.66	-70.45	
	[0.36,0.97]	[-0.15, 0.70]	[0.15, 1.40]	[-98.25,-36.55]	
g	0.34	0.27	0.69	-53.23	
	[-0.05,0.80]	[-0.13, 0.64]	[0.35, 1.81]	[-103.58,-25.84]	
Σ_z					
	x_1	x_2	g	π	
x_1	1	-0.52	0.001	-0.004	
	[1, 1]	[-0.67, 0.06]	[-0.001,0.004]	[-0.005,-0.003]	
x_2		1	0.004	0.0028	
		[1, 1]	[0.002,0.006]	[0.0006,0.0036]	
g			0.00006	0.0000012	
			[0.00004,0.00007]	[-0.000005,0.000007]	
π				0.000027	
				[0.000020,0.000032]	
$\mathbb{Q}$-drift					
	$\mu_z^{\mathbb{Q}}$	$\Phi_z^{\mathbb{Q}}$			
		x_1	x_2	g	π
x_1	0	0.80	0.09	0	0
	[0, 0]	[0.57, 0.88]	[-0.25,0.34]	[0, 0]	[0, 0]
x_2	0	-0.18	0.21	0	0
	[0, 0]	[-0.41, 0.27]	[-0.34, 0.54]	[0, 0]	[0, 0]
g	0.001	-0.003	-0.007	0.95	-0.09
	[-0.000, 0.002]	[-0.006,0.002]	[-0.016,-0.003]	[0.92,0.99]	[-0.18, -0.02]
π	0.0011	0.0006	-0.001	-0.04	0.92
	[0.0006,0.0019]	[0.0002,0.0019]	[-0.003,0.000]	[-0.08, -0.01]	[0.87, 0.96]

Table 2: Parameters NFT4

Real interest rate					
	$\delta_{x,0}$	δ_x			
		x_1	x_2		
	0.007	0.003	-0.0025		
	[0.006, 0.007]	[0.002, 0.004]	[-0.005, -0.001]		
Real risk premia					
	Λ_0	Λ_1			
		x_1	x_2	g	
x_1	0.34	0.09	0.20	-42.97	
	[-0.06, 0.71]	[-0.10, 0.19]	[-0.10, 0.37]	[-65.62, -19.49]	
x_2	0.47	0.17	0.05	-10.58	
	[0.13, 0.68]	[0.03, 0.25]	[-0.22, 0.23]	[-36.60, 19.10]	
g	0.79	0.19	-0.02	-68.05	
	[0.57, 1.22]	[0.09, 0.39]	[-0.36, 0.22]	[-101.82, -53.18]	
Σ_z					
	x_1	x_2	g	π	
x_1	1	0.25	0.005	0.001	
	[1, 1]	[-0.30, 0.73]	[0.003, 0.006]	[-0.002, 0.003]	
x_2		1	0.003	0.0048	
		[1, 1]	[0.001, 0.004]	[0.0000, 0.0054]	
g			0.00006	-0.0000016	
			[0.00005, 0.00007]	[-0.000008, 0.000005]	
π				0.000029	
				[0.000022, 0.000035]	
$\mathbb{Q}$-drift					
	$\mu_z^{\mathbb{Q}}$	$\Phi_z^{\mathbb{Q}}$			
		x_1	x_2	g	π
x_1	0	0.85	-0.18	0	0
	[0, 0]	[0.76, 0.93]	[-0.39, 0.12]	[0, 0]	[0, 0]
x_2	0	-0.10	0.38	0	0
	[0, 0]	[-0.19, 0.04]	[0.23, 0.67]	[0, 0]	[0, 0]
g	-0.005	-0.002	-0.005	1.13	0.56
	[-0.010, -0.003]	[-0.003, -0.001]	[-0.007, -0.003]	[1.07, 1.25]	[0.28, 1.08]
π	0.0027	0.0000	-0.001	-0.07	0.69
	[0.0020, 0.0039]	[-0.0003, 0.0005]	[-0.002, 0.000]	[-0.11, -0.04]	[0.56, 0.77]

Table 3: Parameters OFO4

Σ_z					
	x_1	x_2	g	π	
x_1	1	-0.59	0.002	0.000	
	[1, 1]	[-0.76, 0.69]	[-0.003, 0.004]	[-0.003, 0.002]	
x_2		1	-0.002	-0.0031	
		[1, 1]	[-0.003, -0.001]	[-0.0039, -0.0022]	
g			0.00005	0.0000046	
			[0.00004, 0.00007]	[-0.000002, 0.000011]	
π				0.000027	
				[0.000021, 0.000034]	
$\mathbb{P}$-drift					
	μ_z	Φ_z			
		x_1	x_2	g	π
x_1	0	0.90	0.10	0	0
	[0, 0]	[0.86, 0.93]	[-0.14, 0.15]	[0, 0]	[0, 0]
x_2	0	0.06	0.93	0	0
	[0, 0]	[-0.08, 0.09]	[0.89, 0.96]	[0, 0]	[0, 0]
g	0.006	-0.0005	0.0002	0.29	-0.17
	[0.003, 0.009]	[-0.0010, 0.0007]	[-0.0004, 0.0011]	[0.10, 0.41]	[-0.43, 0.10]
π	0.0056	0.00018	-0.0010	-0.01	0.07
	[0.0012, 0.0101]	[-0.00021, 0.00025]	[-0.0012, -0.0009]	[-0.02, 0.00]	[0.05, 0.09]

Table 4: Parameters OF4

Σ_z					
	x_1	x_2	g	π	
x_1	1	-0.37	0.000	0.001	
	[1, 1]	[-0.78, 0.70]	[-0.002, 0.003]	[-0.003, 0.003]	
x_2		1	-0.002	-0.0032	
		[1, 1]	[-0.003, -0.001]	[-0.0038, -0.0023]	
g			0.00005	0.0000049	
			[0.00004, 0.00006]	[0.0000000, 0.0000097]	
π				0.000023	
				[0.000018, 0.000027]	
$\mathbb{P}$-drift					
	μ_z	Φ_z			
		x_1	x_2	g	π
x_1	-0.69	0.93	0.12	-8.13	-11.97
	[-1.31, 1.09]	[0.81, 0.96]	[-0.16, 0.19]	[-20.84, 17.16]	[-34.19, 16.91]
x_2	0.25	0.02	0.94	11.49	-8.80
	[0.01, 0.87]	[-0.05, 0.08]	[0.87, 0.99]	[-8.27, 29.73]	[-21.75, 5.48]
g	0.001	-0.0004	0.0007	0.25	0.01
	[-0.003, 0.005]	[-0.0009, 0.0006]	[0.0000, 0.0013]	[0.08, 0.35]	[-0.11, 0.09]
π	0.0103	0.0001	-0.0018	0.04	0.00
	[0.0072, 0.0134]	[-0.0002, 0.0003]	[-0.0022, -0.0011]	[-0.04, 0.13]	[-0.16, 0.13]
$\mathbb{P}^1$-drift					
	μ_z^1	Φ_z^1			
		x_1	x_2	g	π
x_1	0	0.70	0.39	0	0
	[0, 0]	[0.07, 1.19]	[-0.49, 0.43]	[0, 0]	[0, 0]
x_2	0	0.45	0.42	0	0
	[0, 0]	[-0.63, 0.81]	[-0.11, 1.04]	[0, 0]	[0, 0]
g	-0.17	0.10	-0.09	0.82	13.24
	[-0.20, -0.12]	[-0.13, 0.17]	[-0.20, 0.04]	[0.79, 0.86]	[7.73, 17.24]
π	0.0068	-0.0002	-0.0014	0.005	-0.12
	[0.0059, 0.0077]	[-0.0004, 0.0003]	[-0.0016, -0.0009]	[0.004, 0.006]	[-0.20, -0.06]
$\mathbb{P}^2$-drift					
	μ_z^2	Φ_z^2			
		x_1	x_2	g	π
x_1	0	0.98	0.02	0	0
	[0, 0]	[0.95, 1.00]	[-0.02, 0.02]	[0, 0]	[0, 0]
x_2	0	0.02	0.97	0	0
	[0, 0]	[-0.03, 0.04]	[0.93, 1.00]	[0, 0]	[0, 0]
g	0.005	0.002	0.0004	0.95	4.75
	[-0.006, 0.013]	[-0.003, 0.004]	[-0.003, 0.003]	[0.93, 0.97]	[3.79, 6.36]
π	0.007	-0.0002	-0.0013	-0.011	0.01
	[0.006, 0.008]	[-0.0004, 0.0002]	[-0.0015, -0.0008]	[-0.013, -0.009]	[-0.01, 0.03]
$\mathbb{P}^3$-drift					
	μ_z^3	Φ_z^3			
		x_1	x_2	g	π
x_1	0	0.96	0.03	0	0
	[0, 0]	[0.91, 1.00]	[-0.04, 0.04]	[0, 0]	[0, 0]
x_2	0	0.03	0.94	0	0
	[0, 0]	[-0.05, 0.06]	[0.89, 0.98]	[0, 0]	[0, 0]
g	-0.27	-0.02	0.04	0.41	-9.20
	[-0.39, -0.15]	[-0.04, 0.03]	[0.01, 0.06]	[0.25, 0.55]	[-16.71, -3.87]
π	0.0064	-0.0002	-0.0013	0.005	0.04
	[0.0055, 0.0072]	[-0.0004, 0.0003]	[-0.0014, -0.0007]	[0.004, 0.006]	[0.01, 0.07]

Table 5: Parameters AO5

Real interest rate						
	$\delta_{x,0}$	δ_x				
		x_1	x_2	x_3		
	0.0049	0.0059	-0.0016	-0.0035		
	[0.0033, 0.0068]	[0.0046, 0.0068]	[-0.0022, -0.0011]	[-0.0042, -0.0026]		
Real risk premia						
	Λ_0	Λ_1				
		x_1	x_2	x_2	g	
x_1	-0.04	-0.10	-0.06	0.20	-6.23	
	[-0.19, 0.09]	[-0.26, 0.03]	[-0.15, 0.02]	[0.07, 0.37]	[-12.32, 2.90]	
x_2	0.11	0.12	0.04	-0.42	-39.13	
	[0.02, 0.21]	[0.03, 0.25]	[-0.03, 0.12]	[-0.64, -0.28]	[-55.75, -30.71]	
x_3	-0.35	-0.62	-0.12	0.82	10.93	
	[-0.61, -0.19]	[-0.90, -0.23]	[-0.30, 0.05]	[0.44, 1.09]	[-8.12, 29.11]	
g	1.19	1.90	0.75	-2.88	-106.51	
	[0.97, 1.59]	[1.21, 2.66]	[0.41, 1.41]	[-3.74, -2.25]	[-134.83, -93.43]	
Σ_z						
	x_1	x_2	x_3	g	π	
x_1	1	0.75	0.89	-0.0010	-0.0048	
	[1, 1]	[0.49, 0.86]	[0.86, 0.91]	[-0.0017, -0.0001]	[-0.0052, -0.0044]	
x_2		1	0.74	-0.0011	-0.0042	
		[1, 1]	[0.51, 0.83]	[-0.002, 0.000]	[-0.0048, -0.0030]	
x_3			1	-0.0022	-0.0050	
			[1, 1]	[-0.003, -0.001]	[-0.0053, -0.0046]	
g				0.000056	0.0000052	
				[0.000045, 0.000064]	[0.0000005, 0.0000081]	
π					0.000027	
					[0.000023, 0.000030]	
$\mathbb{Q}$-drift						
	$\mu_z^{\mathbb{Q}}$	$\Phi_z^{\mathbb{Q}}$				
		x_1	x_2	x_3	g	π
x_1	0	0.83	0.09	-0.72	0	0
	[0, 0]	[0.65, 0.94]	[0.03, 0.16]	[-0.84, -0.56]	[0, 0]	[0, 0]
x_2	0	-0.14	0.92	-0.42	0	0
	[0, 0]	[-0.28, -0.05]	[0.87, 0.98]	[-0.57, -0.13]	[0, 0]	[0, 0]
x_3	0	0.16	0.16	-0.34	0	0
	[0, 0]	[-0.09, 0.34]	[0.06, 0.28]	[-0.49, -0.12]	[0, 0]	[0, 0]
g	-0.002	-0.014	-0.005	0.021	1.03	-0.13
	[-0.004, -0.001]	[-0.019, -0.008]	[-0.009, -0.003]	[0.016, 0.027]	[1.02, 1.06]	[-0.18, -0.10]
π	0.000	0.0008	-0.0001	0.0038	0.00	0.99
	[0.000, 0.000]	[0.0001, 0.0017]	[-0.0005, 0.0002]	[0.0028, 0.0044]	[-0.00, 0.00]	[0.99, 1.00]

Table 6: Parameters AOT5

Real interest rate						
	$\delta_{x,0}$	δ_x				
		x_1	x_2	x_3		
	0.0104	0.0056	-0.0012	-0.0034		
	[0.0091, 0.0118]	[0.0043, 0.0064]	[-0.0018, -0.0007]	[-0.0039, -0.0026]		
Real risk premia						
	Λ_0	Λ_1				
		x_1	x_2	x_2	g	
x_1	3.50	0.46	0.21	-0.83	11.64	
	[2.62, 4.26]	[0.11, 0.70]	[0.12, 0.35]	[-1.04, -0.55]	[0.62, 17.33]	
x_2	1.55	0.08	-0.03	-0.27	-29.64	
	[0.65, 2.53]	[-0.04, 0.22]	[-0.11, 0.04]	[-0.49, -0.09]	[-43.45, -18.52]	
x_3	4.58	0.52	0.37	-1.11	13.65	
	[3.66, 5.67]	[0.29, 0.79]	[0.21, 0.61]	[-1.34, -0.92]	[1.66, 33.16]	
g	11.21	1.61	0.68	-2.79	52.05	
	[10.46, 12.04]	[0.61, 2.29]	[0.40, 1.10]	[-3.26, -2.14]	[32.22, 64.49]	
Σ_z						
	x_1	x_2	x_3	g	π	
x_1	1	0.64	0.88	0.0020	-0.0043	
	[1, 1]	[0.26, 0.80]	[0.83, 0.91]	[0.0006, 0.0029]	[-0.0050, -0.0037]	
x_2		1	0.64	0.0005	-0.0037	
		[1, 1]	[0.32, 0.77]	[-0.001, 0.002]	[-0.0046, -0.0022]	
x_3			1	0.0024	-0.0045	
			[1, 1]	[0.001, 0.003]	[-0.0051, -0.0039]	
g				0.000060	0.0000055	
				[0.000048, 0.000071]	[0.0000015, 0.0000121]	
π					0.000027	
					[0.000021, 0.000033]	
$\mathbb{Q}$-drift						
	$\mu_z^{\mathbb{Q}}$	$\Phi_z^{\mathbb{Q}}$				
		x_1	x_2	x_3	g	π
x_1	0	0.32	-0.16	0.34	0	0
	[0, 0]	[0.09, 0.57]	[-0.27, -0.08]	[0.17, 0.50]	[0, 0]	[0, 0]
x_2	0	-0.42	0.77	0.25	0	0
	[0, 0]	[-0.59, -0.19]	[0.66, 0.85]	[0.08, 0.38]	[0, 0]	[0, 0]
x_3	0	-0.77	-0.25	1.39	0	0
	[0, 0]	[-1.07, -0.46]	[-0.40, -0.15]	[1.19, 1.57]	[0, 0]	[0, 0]
g	-0.075	-0.012	-0.006	0.021	-0.02	-0.42
	[-0.086, -0.058]	[-0.017, -0.004]	[-0.009, -0.003]	[0.015, 0.025]	[-0.08, 0.04]	[-0.58, -0.27]
π	-0.019	0.0004	-0.0003	0.0036	-0.26	0.88
	[-0.022, -0.015]	[-0.0001, 0.0014]	[-0.0007, 0.0000]	[0.0028, 0.0041]	[-0.31, -0.22]	[0.84, 0.92]

Table 7: Parameters AS5

Real interest rate						
	$\delta_{x,0}$	δ_x				
		x_1	x_2	x_3		
	0.0019	0.0062	-0.0004	-0.0048		
	[0.0004, 0.0037]	[0.0052, 0.0067]	[-0.0008, -0.0001]	[-0.0051, -0.0040]		
Real risk premia						
	Λ_0	Λ_1				
		x_1	x_2	x_2	g	
x_1	-0.02	-0.62	-0.10	0.74	-3.63	
	[-0.13, 0.14]	[-0.81, -0.47]	[-0.20, -0.01]	[0.55, 0.94]	[-15.30, 9.81]	
x_2	0.20	-0.60	-0.15	0.61	-9.87	
	[0.05, 0.55]	[-0.74, -0.36]	[-0.30, -0.08]	[0.34, 0.81]	[-30.71, -0.62]	
x_3	-0.24	-0.30	0.14	0.13	-8.81	
	[-0.60, -0.07]	[-0.45, -0.04]	[0.03, 0.32]	[-0.21, 0.30]	[-23.54, 8.95]	
g	0.10	3.57	0.44	-3.86	-90.98	
	[-0.24, 0.53]	[3.06, 3.95]	[0.24, 0.72]	[-4.42, -3.35]	[-113.73, -76.86]	
Σ_z						
	x_1	x_2	x_3	g	π	
x_1	1	0.61	0.91	-0.0014	-0.0043	
	[1, 1]	[0.38, 0.76]	[0.88, 0.92]	[-0.0016, -0.0012]	[-0.0044, -0.0041]	
x_2		1	0.67	-0.0027	-0.0033	
		[1, 1]	[0.47, 0.78]	[-0.003, -0.002]	[-0.0038, -0.0022]	
x_3			1	-0.0020	-0.0044	
			[1, 1]	[-0.002, -0.002]	[-0.0045, -0.0042]	
g				0.000058	0.0000031	
				[0.000054, 0.000061]	[0.0000029, 0.0000034]	
π					0.000021	
					[0.000019, 0.000023]	
$\mathbb{Q}$-drift						
	$\mu_z^{\mathbb{Q}}$	$\Phi_z^{\mathbb{Q}}$				
		x_1	x_2	x_3	g	π
x_1	0	1.38	0.34	-1.39	0	0
	[0, 0]	[1.17, 1.50]	[0.26, 0.43]	[-1.52, -1.22]	[0, 0]	[0, 0]
x_2	0	0.90	1.17	-1.52	0	0
	[0, 0]	[0.64, 1.04]	[1.06, 1.31]	[-1.72, -1.17]	[0, 0]	[0, 0]
x_3	0	0.62	0.35	-0.82	0	0
	[0, 0]	[0.38, 0.76]	[0.26, 0.47]	[-0.96, -0.62]	[0, 0]	[0, 0]
g	0.012	-0.027	-0.004	0.028	0.79	-0.55
	[0.009, 0.016]	[-0.030, -0.023]	[-0.006, -0.003]	[0.023, 0.031]	[0.78, 0.80]	[-0.60, -0.50]
π	-0.0011	-0.0002	-0.0011	0.0050	0.022	1.051
	[-0.0014, -0.0008]	[-0.0005, 0.0006]	[-0.0015, -0.0009]	[0.0042, 0.0054]	[0.021, 0.022]	[1.046, 1.056]
$\mathbb{P}^1$-drift						
	μ_z^1	Φ_z^1				
		x_1	x_2	x_3	g	π
x_1	-0.71	0.12	0.21	-0.38	-44.93	0
	[-1.35, -0.14]	[-0.28, 0.46]	[-0.00, 0.44]	[-0.79, 0.15]	[-83.86, -7.49]	[0, 0]
x_2	1.48	0.26	0.64	-0.27	34.22	0
	[0.80, 2.34]	[-0.24, 0.82]	[0.43, 0.82]	[-0.68, 0.13]	[-20.62, 93.01]	[0, 0]
x_3	1.15	-0.92	0.10	-0.05	39.82	0
	[0.87, 1.56]	[-1.32, -0.67]	[-0.04, 0.24]	[-0.37, 0.32]	[20.48, 69.15]	[0, 0]
g	0.01	0.016	-0.001	-0.007	-0.92	-0.55
	[-0.00, 0.02]	[0.008, 0.026]	[-0.005, 0.002]	[-0.018, 0.000]	[-1.72, -0.34]	[-0.60, -0.50]
π	-0.004	0.0016	-0.00013	0.0043	0.13	1.051
	[-0.006, -0.003]	[0.0010, 0.0027]	[-0.0005, 0.0002]	[0.0032, 0.0053]	[0.07, 0.19]	[1.046, 1.056]
$\mathbb{P}^2$-drift						
	μ_z^2	Φ_z^2				
		x_1	x_2	x_3	g	π
x_1	0.44	0.65	0.09	-0.67	5.11	0
	[0.27, 0.61]	[0.43, 0.78]	[-0.01, 0.17]	[-0.82, -0.46]	[-5.22, 19.51]	[0, 0]
x_2	0.68	-0.22	0.81	-0.54	-34.35	0
	[0.44, 0.92]	[-0.40, -0.05]	[0.72, 0.89]	[-0.76, -0.29]	[-50.06, -19.07]	[0, 0]
x_3	0.59	-0.17	0.01	0.07	-22.45	0
	[0.39, 0.79]	[-0.34, -0.01]	[-0.08, 0.08]	[-0.11, 0.27]	[-31.05, -10.13]	[0, 0]
g	0.00	0.002	0.001	0.001	0.86	-0.55
	[-0.00, 0.01]	[-0.004, 0.006]	[-0.001, 0.004]	[-0.004, 0.008]	[0.45, 1.09]	[-0.60, -0.50]
π	-0.003	0.0007	-0.00006	0.0036	0.10	1.051
	[-0.004, -0.002]	[0.0004, 0.0012]	[-0.0003, 0.0001]	[0.0030, 0.0039]	[0.09, 0.11]	[1.046, 1.056]
$\mathbb{P}^3$-drift						
	μ_z^3	Φ_z^3				
		x_1	x_2	x_3	g	π
x_1	5.93	-4.04	-1.19	3.14	-168.34	0
	[5.09, 6.70]	[-4.53, -3.25]	[-1.64, -0.81]	[1.96, 4.08]	[-184.24, -149.32]	[0, 0]
x_2	-2.55	2.79	1.58	-2.77	80.21	0
	[-5.22, -0.47]	[0.82, 5.23]	[1.09, 2.04]	[-4.41, -1.26]	[18.65, 155.46]	[0, 0]
x_3	0.82	-0.75	-0.03	0.51	-34.25	0
	[-0.17, 1.30]	[-1.13, -0.08]	[-0.15, 0.21]	[-0.03, 0.87]	[-45.66, -8.82]	[0, 0]
g	-0.04	0.050	0.011	-0.038	2.14	-0.55
	[-0.05, -0.03]	[0.036, 0.061]	[0.007, 0.016]	[-0.050, -0.022]	[1.77, 2.47]	[-0.60, -0.50]
π	-0.003	0.0008	-0.00007	0.0034	0.13	1.051
	[-0.004, -0.002]	[0.0005, 0.0013]	[-0.0003, 0.0001]	[0.0029, 0.0037]	[0.12, 0.14]	[1.046, 1.056]

Table 8: Parameters AST5

Real interest rate						
	$\delta_{x,0}$	δ_x				
		x_1	x_2	x_3		
	0.0087	0.0059	-0.0010	-0.0044		
	[0.0080, 0.0095]	[0.0050, 0.0064]	[-0.0012, -0.0006]	[-0.0048, -0.0039]		
Real risk premia						
	Λ_0	Λ_1				
		x_1	x_2	x_2	g	
x_1	-0.47	-0.41	0.05	0.52	-2.83	
	[-0.71, -0.38]	[-0.53, -0.29]	[-0.06, 0.10]	[0.37, 0.67]	[-14.99, 9.51]	
x_2	-0.03	0.03	-0.09	0.04	-15.96	
	[-0.30, 0.23]	[-0.05, 0.18]	[-0.23, -0.05]	[-0.17, 0.20]	[-35.68, -3.96]	
x_3	-0.13	-0.23	0.13	0.19	-9.99	
	[-0.37, 0.23]	[-0.32, 0.00]	[0.02, 0.26]	[-0.09, 0.34]	[-25.87, 6.21]	
g	3.34	1.87	0.43	-2.60	-78.54	
	[2.89, 4.16]	[1.53, 2.14]	[0.33, 0.67]	[-3.02, -2.23]	[-102.81, -67.19]	
Σ_z						
	x_1	x_2	x_3	g	π	
x_1	1	0.39	0.89	-0.0012	-0.0042	
	[1, 1]	[0.01, 0.65]	[0.86, 0.91]	[-0.0015, -0.0009]	[-0.0044, -0.0040]	
x_2		1	0.46	-0.0018	-0.0024	
		[1, 1]	[0.16, 0.69]	[-0.002, -0.001]	[-0.0035, -0.0008]	
x_3			1	-0.0018	-0.0044	
			[1, 1]	[-0.002, -0.002]	[-0.0046, -0.0041]	
g				0.000058	0.0000030	
				[0.000050, 0.000062]	[0.0000027, 0.0000033]	
π					0.000021	
					[0.000019, 0.000022]	
$\mathbb{Q}$-drift						
	$\mu_z^{\mathbb{Q}}$	$\Phi_z^{\mathbb{Q}}$				
		x_1	x_2	x_3	g	π
x_1	0	1.19	0.13	-1.13	0	0
	[0, 0]	[1.04, 1.27]	[0.10, 0.21]	[-1.21, -1.01]	[0, 0]	[0, 0]
x_2	0	0.26	0.97	-0.70	0	0
	[0, 0]	[0.13, 0.32]	[0.92, 1.05]	[-0.97, -0.26]	[0, 0]	[0, 0]
x_3	0	0.35	0.14	-0.53	0	0
	[0, 0]	[0.16, 0.45]	[0.09, 0.24]	[-0.62, -0.40]	[0, 0]	[0, 0]
g	-0.015	-0.014	-0.003	0.017	0.73	-0.50
	[-0.019, -0.011]	[-0.015, -0.011]	[-0.005, -0.002]	[0.014, 0.020]	[0.71, 0.74]	[-0.57, -0.44]
π	0.0012	-0.0003	-0.0003	0.0046	0.018	1.029
	[0.0009, 0.0015]	[-0.0006, 0.0003]	[-0.0006, -0.0001]	[0.0041, 0.0049]	[0.017, 0.019]	[1.024, 1.034]
$\mathbb{P}^1$-drift						
	μ_z^1	Φ_z^1				
		x_1	x_2	x_3	g	π
x_1	-3.36	-0.01	0.07	-0.19	-75.04	0
	[-4.44, -2.39]	[-0.30, 0.24]	[-0.08, 0.24]	[-0.62, 0.19]	[-95.44, -29.71]	[0, 0]
x_2	2.21	0.69	0.79	-0.50	58.36	0
	[0.25, 4.60]	[0.18, 1.23]	[0.57, 0.95]	[-1.04, 0.13]	[-4.59, 107.28]	[0, 0]
x_3	-1.55	-0.44	0.03	-0.05	14.37	0
	[-1.94, -1.06]	[-0.58, -0.32]	[-0.03, 0.11]	[-0.27, 0.11]	[3.37, 37.47]	[0, 0]
g	0.06	0.012	-0.001	-0.004	0.11	-0.50
	[0.04, 0.07]	[0.007, 0.015]	[-0.004, 0.002]	[-0.009, 0.001]	[-0.57, 0.42]	[-0.57, -0.44]
π	0.003	0.0010	0.00004	0.0038	0.10	1.029
	[0.002, 0.004]	[0.0007, 0.0016]	[-0.0002, 0.0002]	[0.0031, 0.0043]	[0.08, 0.13]	[1.024, 1.034]
$\mathbb{P}^2$-drift						
	μ_z^2	Φ_z^2				
		x_1	x_2	x_3	g	π
x_1	-0.63	0.80	0.06	-0.84	-0.22	0
	[-0.92, -0.38]	[0.66, 0.89]	[-0.00, 0.13]	[-1.08, -0.61]	[-7.62, 8.75]	[0, 0]
x_2	-0.95	-0.25	0.84	-0.33	-28.78	0
	[-1.25, -0.60]	[-0.36, -0.14]	[0.78, 0.90]	[-0.66, 0.09]	[-42.49, -17.71]	[0, 0]
x_3	-0.70	-0.20	0.02	0.14	-14.91	0
	[-0.92, -0.52]	[-0.31, -0.08]	[-0.05, 0.08]	[-0.04, 0.29]	[-20.27, -11.28]	[0, 0]
g	0.01	0.002	0.000	0.002	0.80	-0.50
	[0.01, 0.02]	[-0.003, 0.004]	[-0.002, 0.003]	[-0.002, 0.010]	[0.72, 0.89]	[-0.57, -0.44]
π	0.002	0.0008	-0.00005	0.0034	0.08	1.029
	[0.002, 0.003]	[0.0006, 0.0012]	[-0.0002, 0.0001]	[0.0029, 0.0036]	[0.07, 0.09]	[1.024, 1.034]
$\mathbb{P}^3$-drift						
	μ_z^3	Φ_z^3				
		x_1	x_2	x_3	g	π
x_1	-4.71	-2.38	-0.76	2.09	-8.52	0
	[-5.80, -3.69]	[-2.98, -1.64]	[-1.22, -0.47]	[1.51, 2.67]	[-19.54, 2.31]	[0, 0]
x_2	4.23	3.23	1.65	-3.26	-34.81	0
	[1.57, 7.20]	[1.15, 5.41]	[1.22, 2.20]	[-4.77, -1.70]	[-52.28, -21.36]	[0, 0]
x_3	-1.79	-0.81	-0.08	0.62	-11.29	0
	[-2.24, -1.13]	[-1.09, -0.36]	[-0.19, 0.09]	[0.21, 0.91]	[-16.67, -6.39]	[0, 0]
g	0.08	0.045	0.010	-0.036	0.44	-0.50
	[0.05, 0.10]	[0.030, 0.057]	[0.006, 0.017]	[-0.048, -0.023]	[0.24, 0.63]	[-0.57, -0.44]
π	0.002	0.0008	-0.00005	0.0033	0.11	1.029
	[0.001, 0.003]	[0.0006, 0.0012]	[-0.0002, 0.0001]	[0.0028, 0.0035]	[0.10, 0.13]	[1.024, 1.034]