A Appendix — Additional Information/Results

A.1 The Smets-Wouters Model

We begin by briefly describing the log-linearized equilibrium conditions of the Smets and Wouters (2007) model. We follow Del Negro and Schorfheide (forthcoming) and detrend the non-stationary model variables by a stochastic rather than a deterministic trend.[28] Let $\tilde{z}_t$ be the linearly detrended log productivity process which follows the autoregressive law of motion

$$\tilde{z}_t = \rho_z \tilde{z}_{t-1} + \sigma_z \varepsilon_{z,t}. \tag{26}$$

We detrend all non stationary variables by $Z_t = e^{\gamma t + \frac{1}{1-\alpha}\tilde{z}_t}$, where γ is the steady state growth rate of the economy. The growth rate of Z_t in deviations from γ, denoted by z_t, follows the process:

$$z_t = \ln(Z_t/Z_{t-1}) - \gamma = \frac{1}{1-\alpha}(\rho_z - 1)\tilde{z}_{t-1} + \frac{1}{1-\alpha}\sigma_z \epsilon_{z,t}. \tag{27}$$

All variables in the following equations are expressed in log deviations from their non-stochastic steady state. Steady state values are denoted by $*$-subscripts and steady state formulas are provided in the technical appendix of Del Negro and Schorfheide (forthcoming).[29] The consumption Euler equation is given by:

$$c_t = -\frac{(1-he^{-\gamma})}{\sigma_c(1+he^{-\gamma})}\left(R_t - \mathbb{E}_t[\pi_{t+1}] + b_t\right) + \frac{he^{-\gamma}}{(1+he^{-\gamma})}\left(c_{t-1} - z_t\right) + \frac{1}{(1+he^{-\gamma})}\mathbb{E}_t\left[c_{t+1} + z_{t+1}\right] + \frac{(\sigma_c - 1)}{\sigma_c(1+he^{-\gamma})}\frac{w_* L_*}{c_*}\left(L_t - \mathbb{E}_t[L_{t+1}]\right), \tag{28}$$

where c_t is consumption, L_t is labor supply, R_t is the nominal interest rate, and π_t is inflation. The exogenous process b_t drives a wedge between the intertemporal ratio of the marginal utility of consumption and the riskless real return $R_t - \mathbb{E}_t[\pi_{t+1}]$, and follows an AR(1) process with parameters ρ_b and σ_b. The parameters σ_c and h capture the relative degree of risk aversion and the degree of habit persistence in the utility function, respectively. The following condition expresses the relationship between the value of capital in

[28] This approach makes it possible to express almost all equilibrium conditions in a way that encompasses both the trend-stationary total factor productivity process in Smets and Wouters (2007), as well as the case where technology follows a unit root process.

[29] Available at `http://economics.sas.upenn.edu/~schorf/research.htm`.

terms of consumption q_t^k and the level of investment i_t measured in terms of consumption goods:

$$q_t^k = S'' e^{2\gamma}(1+\beta e^{(1-\sigma_c)\gamma})\Big(i_t - \frac{1}{1+\beta e^{(1-\sigma_c)\gamma}}(i_{t-1} - z_t) - \frac{\beta e^{(1-\sigma_c)\gamma}}{1+\beta e^{(1-\sigma_c)\gamma}} \mathbb{E}_t\left[i_{t+1} + z_{t+1}\right] - \mu_t\Big), \quad (29)$$

which is affected by both investment adjustment cost (S'' is the second derivative of the adjustment cost function) and by μ_t, an exogenous process called the "marginal efficiency of investment" that affects the rate of transformation between consumption and installed capital (see Greenwood et al. (1998)). The exogenous process μ_t follows an AR(1) process with parameters ρ_μ and σ_μ. The parameter β captures the intertemporal discount rate in the utility function of the households.

The capital stock, $\bar{k}_t$, evolves as

$$\bar{k}_t = \left(1 - \frac{i_*}{\bar{k}_*}\right)\left(\bar{k}_{t-1} - z_t\right) + \frac{i_*}{\bar{k}_*} i_t + \frac{i_*}{\bar{k}_*} S'' e^{2\gamma}(1+\beta e^{(1-\sigma_c)\gamma})\mu_t, \quad (30)$$

where $i_*/\bar{k}_*$ is the steady state ratio of investment to capital. The arbitrage condition between the return to capital and the riskless rate is:

$$\frac{r_*^k}{r_*^k + (1-\delta)} \mathbb{E}_t[r_{t+1}^k] + \frac{1-\delta}{r_*^k + (1-\delta)} \mathbb{E}_t[q_{t+1}^k] - q_t^k = R_t + b_t - \mathbb{E}_t[\pi_{t+1}], \quad (31)$$

where r_t^k is the rental rate of capital, r_*^k its steady state value, and δ the depreciation rate. Given that capital is subject to variable capacity utilization u_t, the relationship between $\bar{k}_t$ and the amount of capital effectively rented out to firms k_t is

$$k_t = u_t - z_t + \bar{k}_{t-1}. \quad (32)$$

The optimality condition determining the rate of utilization is given by

$$\frac{1-\psi}{\psi} r_t^k = u_t, \quad (33)$$

where ψ captures the utilization costs in terms of foregone consumption. Real marginal costs for firms are given by

$$mc_t = w_t + \alpha L_t - \alpha k_t, \quad (34)$$

where α is the income share of capital (after paying markups and fixed costs) in the production function. From the optimality conditions of goods producers it follows that all firms have the same capital-labor ratio:

$$k_t = w_t - r_t^k + L_t. \quad (35)$$

The production function is:

$$y_t \;=\; \Phi_p\left(\alpha k_t + (1-\alpha)L_t\right) + \mathcal{I}\{\rho_z < 1\}(\Phi_p - 1)\frac{1}{1-\alpha}\tilde{z}_t, \tag{36}$$

under trend stationarity. The last term $(\Phi_p - 1)\frac{1}{1-\alpha}\tilde{z}_t$ drops out if technology has a stochastic trend, because in this case one has to assume that the fixed costs are proportional to the trend. Similarly, the resource constraint is:

$$y_t = g_t + \frac{c_*}{y_*}c_t + \frac{i_*}{y_*}i_t + \frac{r_*^k k_*}{y_*}u_t - \mathcal{I}\{\rho_z < 1\}\frac{1}{1-\alpha}\tilde{z}_t, \tag{37}$$

where again the term $-\frac{1}{1-\alpha}\tilde{z}_t$ disappears if technology follows a unit root process. Government spending g_t is assumed to follow the exogenous process:

$$g_t = \rho_g g_{t-1} + \sigma_g \varepsilon_{g,t} + \eta_{gz}\sigma_z\varepsilon_{z,t}.$$

Finally, the price and wage Phillips curves are, respectively:

$$\begin{aligned}\pi_t = {} & \frac{(1-\zeta_p\beta e^{(1-\sigma_c)\gamma})(1-\zeta_p)}{(1+\iota_p\beta e^{(1-\sigma_c)\gamma})\zeta_p((\Phi_p-1)\epsilon_p+1)} mc_t \\ & + \frac{\iota_p}{1+\iota_p\beta e^{(1-\sigma_c)\gamma}}\pi_{t-1} + \frac{\beta e^{(1-\sigma_c)\gamma}}{1+\iota_p\beta e^{(1-\sigma_c)\gamma}}I\!E_t[\pi_{t+1}] + \lambda_{f,t},\end{aligned} \tag{38}$$

and

$$\begin{aligned}w_t = {} & \frac{(1-\zeta_w\beta e^{(1-\sigma_c)\gamma})(1-\zeta_w)}{(1+\beta e^{(1-\sigma_c)\gamma})\zeta_w((\lambda_w-1)\epsilon_w+1)}\left(w_t^h - w_t\right) \\ & - \frac{1+\iota_w\beta e^{(1-\sigma_c)\gamma}}{1+\beta e^{(1-\sigma_c)\gamma}}\pi_t + \frac{1}{1+\beta e^{(1-\sigma_c)\gamma}}\left(w_{t-1} - z_t - \iota_w\pi_{t-1}\right) \\ & + \frac{\beta e^{(1-\sigma_c)\gamma}}{1+\beta e^{(1-\sigma_c)\gamma}}I\!E_t\left[w_{t+1} + z_{t+1} + \pi_{t+1}\right] + \lambda_{w,t},\end{aligned} \tag{39}$$

where ζ_p, ι_p, and ϵ_p are the Calvo parameter, the degree of indexation, and the curvature parameters in the Kimball aggregator for prices, and ζ_w, ι_w, and ϵ_w are the corresponding parameters for wages. w_t^h measures the household's marginal rate of substitution between consumption and labor, and is given by:

$$w_t^h = \frac{1}{1-he^{-\gamma}}\left(c_t - he^{-\gamma}c_{t-1} + he^{-\gamma}z_t\right) + \nu_l L_t, \tag{40}$$

where ν_l characterizes the curvature of the disutility of labor (and would equal the inverse of the Frisch elasticity in absence of wage rigidities). The mark-ups $\lambda_{f,t}$ and $\lambda_{w,t}$ follow exogenous ARMA(1,1) processes

$$\lambda_{f,t} = \rho_{\lambda_f}\lambda_{f,t-1} + \sigma_{\lambda_f}\varepsilon_{\lambda_f,t} + \eta_{\lambda_f}\sigma_{\lambda_f}\varepsilon_{\lambda_f,t-1}, \text{ and}$$

$$\lambda_{w,t} = \rho_{\lambda_w}\lambda_{w,t-1} + \sigma_{\lambda_w}\varepsilon_{\lambda_w,t} + \eta_{\lambda_w}\sigma_{\lambda_w}\varepsilon_{\lambda_w,t-1},$$

respectively. Finally, the monetary authority follows a generalized feedback rule:

$$\begin{aligned} R_t &= \rho_R R_{t-1} + (1-\rho_R)\left(\psi_1\pi_t + \psi_2(y_t - y_t^f)\right) \\ &\quad +\psi_3\left((y_t - y_t^f) - (y_{t-1} - y_{t-1}^f)\right) + r_t^m, \end{aligned} \tag{41}$$

where the flexible price/wage output y_t^f is obtained from solving the version of the model without nominal rigidities (that is, Equations (28) through (37) and (40)), and the residual r_t^m follows an AR(1) process with parameters ρ_{r^m} and σ_{r^m}. We use the method in Sims (2002) to solve the log-linear approximation of the DSGE model.

The measurement equations (equation) for real output, consumption, investment, and real wage growth, hours, inflation, and interest rates are given by:

$$\begin{aligned} \textit{Output growth} &= \gamma + 100\,(y_t - y_{t-1} + z_t) \\ \textit{Consumption growth} &= \gamma + 100\,(c_t - c_{t-1} + z_t) \\ \textit{Investment growth} &= \gamma + 100\,(i_t - i_{t-1} + z_t) \\ \textit{Real Wage growth} &= \gamma + 100\,(w_t - w_{t-1} + z_t)\ , \\ \textit{Hours} &= \bar{l} + 100 l_t \\ \textit{Inflation} &= \pi_* + 100\pi_t \\ \textit{FFR} &= R_* + 100 R_t \end{aligned} \tag{42}$$

where all variables are measured in percent, and the parameters π_* and R_* measure the steady state level of net inflation and short term nominal interest rates, respectively and where $\bar{l}$ captures the mean of hours (this variable is measured as an index).

A.2 Data

The data set is obtained from Haver Analytics (Haver mnemonics are in italics). We compile observations for the variables that appear in the measurement equation (42). Real GDP (GDPC), the GDP price deflator (GDPDEF), nominal personal consumption expenditures (PCEC), and nominal fixed private investment (FPI) are constructed at a quarterly frequency by the Bureau of Economic Analysis (BEA), and are included in the National Income and Product Accounts (NIPA).

Average weekly hours of production and non-supervisory employees for total private industries (PRS85006023), civilian employment (CE16OV), and civilian noninstitutional population (LNSINDEX) are produced by the Bureau of Labor Statistics (BLS) at the monthly frequency. The first of these series is obtained from the Establishment Survey, and the remaining from the Household Survey. Both surveys are released in the BLS Employment Situation Summary (ESS). Since our models are estimated on quarterly data, we take averages of the monthly data. Compensation per hour for the non-farm business sector (PRS85006103) is obtained from the Labor Productivity and Costs (LPC) release, and produced by the BLS at the quarterly frequency. Last, the federal funds rate is obtained from the Federal Reserve Board's H.15 release at the business day frequency, and is not revised. We take quarterly averages of the annualized daily data.

All data are transformed following Smets and Wouters (2007). Specifically:

$$\begin{aligned}
\textit{Output growth} &= LN((GDPC)/LNSINDEX) * 100 \\
\textit{Consumption growth} &= LN((PCEC/GDPDEF)/LNSINDEX) * 100 \\
\textit{Investment growth} &= LN((FPI/GDPDEF)/LNSINDEX) * 100 \\
\textit{Real Wage growth} &= LN(PRS85006103/GDPDEF) * 100 \\
\textit{Hours} &= LN((PRS85006023 * CE16OV/100)/LNSINDEX) * 100 \\
\textit{Inflation} &= LN(GDPDEF/GDPDEF(-1)) * 100 \\
\textit{FFR} &= FEDERAL\ FUNDS\ RATE/4
\end{aligned}$$

A.3 Drawing the stochastic volatilities

A.3.1 The KSC Version

The sampler is slightly different depending on the approach for drawing the stochastic volatilities, which are obtained from:

$$p(\varepsilon_{1:T}|\tilde{h}_{1:T}, \tilde{\sigma}_{1:T}, \theta)p(\tilde{\sigma}_{1:T}|\rho_{1:\bar{q}}, \omega^2_{1:\bar{q}}). \tag{43}$$

In this section we describe the sampler under the KSC approach, and in the next section we consider the JPR approach. The key insight of KSC is that if $p(\varepsilon_{1:T}|\tilde{h}_{1:T}, \tilde{\sigma}_{1:T}, \theta)$ in (43) were linear in $\tilde{\sigma}_{1:T}$ and Gaussian, one could use standard state-space methods for drawing $\tilde{\sigma}_{1:T}$. In fact, taking squares and then logs of (3) one can see that $\varepsilon^*_{q,t} = \log(\sigma_q^{-2}\tilde{h}_{q,t}\varepsilon^2_{q,t} + c)$ (where $c = .001$ is an offset constant) is linear in $\sigma_{q,t}$:

$$\varepsilon^*_{q,t} = 2\tilde{\sigma}_{q,t} + \eta^*_{q,t}, \;\; \eta^*_{q,t} \simeq \log(\eta^2_{q,t}), \tag{44}$$

but is not Gaussian, since $\eta^*_{q,t} \sim \log(\chi^2_1)$. KSC suggest approximating the distribution of $\eta^*_{q,t}$ using a mixture of normals:[30]

$$p(\eta^*_{q,t}) \simeq \sum_{k=1}^{K} \pi^*_k \mathcal{N}(m^*_k, \nu^{*\,2}_k), \tag{45}$$

or equivalently, $\eta^*_{q,t} \,|\, \varsigma_{q,t} = k \sim \mathcal{N}(m^*_k - 1.2704, \nu^{*\,2}_k)$, $Pr(\varsigma_{q,t} = k) = \pi^*_k$.

Call $\vartheta = \{\theta, s_{1:T}, \tilde{h}_{1:T}, \lambda_{1:\bar{q}}, \rho_{1:\bar{q}}, \omega^2_{1:\bar{q}}, \varepsilon_{1:T}\}$ all unobservables other than $\varsigma_{1:T}$ and $\tilde{\sigma}_{1:T}$. Del Negro and Primiceri (2013) recognize that in standard macro models it is often difficult to draw from $p(\vartheta|\tilde{\sigma}_{1:T}, \varsigma_{1:T}, y_{1:T})$, and that therefore a Gibbs sampler such as the following one would not work: i) draw ϑ from $\vartheta|\tilde{\sigma}_{1:T}, \varsigma_{1:T}, y_{1:T}$, ii) draw $\tilde{\sigma}_{1:T}$ from $\tilde{\sigma}_{1:T}|\vartheta, \varsigma_{1:T}, y_{1:T}$, iii) draw $\varsigma_{1:T}$ from $\varsigma_{1:T}|\tilde{\sigma}_{1:T}, \vartheta, y_{1:T}$.[31] They suggest the following sampler instead:

(1) draw $\tilde{\sigma}_{1:T}$ from $\tilde{\sigma}_{1:T}|\vartheta, \varsigma_{1:T}, y_{1:T}$;

(2) draw $\vartheta, \varsigma_{1:T}$ from $\vartheta, \varsigma_{1:T}|\tilde{\sigma}_{1:T}, y_{1:T}$, which can be divided into two substeps:

  (2-1) draw ϑ from the marginal $\vartheta|\tilde{\sigma}_{1:T}, y_{1:T}$;

  (2-2) draw $\varsigma_{1:T}$ from the conditional $\varsigma_{1:T}|\vartheta, \tilde{\sigma}_{1:T}, y_{1:T}$.

A.3.2 The JPR Version

Under the JPR approach the volatilities can be drawn directly from (43). The Gibbs sampler is therefore simply:

(1) draw $\tilde{\sigma}_{1:T}$ from $\tilde{\sigma}_{1:T}|\vartheta, y_{1:T}$;

(2) draw ϑ from $\vartheta|\tilde{\sigma}_{1:T}, y_{1:T}$.

For step (1), $\tilde{\sigma}_{1:T}$ is drawn in an additional Gibbs step, in which each $\tilde{\sigma}_t$ is drawn conditional on $(\theta, y_{1:T}, \tilde{\sigma}_{-t})$, where $\tilde{\sigma}_{-t}$ contains all elements of $\tilde{\sigma}_{1:T}$ except for $\tilde{\sigma}_t$. Each $\tilde{\sigma}_t$ is drawn from

[30] We follow Omori et al. (2007) in using a 10-mixture approximation, as opposed to the 7-mixture approximation adopted in Kim et al. (1998). The parameters that optimize this approximation, namely $\{\pi^*_k, m^*_k, \nu^*_k\}_{k=1}^K$, are given in Omori et al. (2007). Note that these parameters are independent of the specific application.

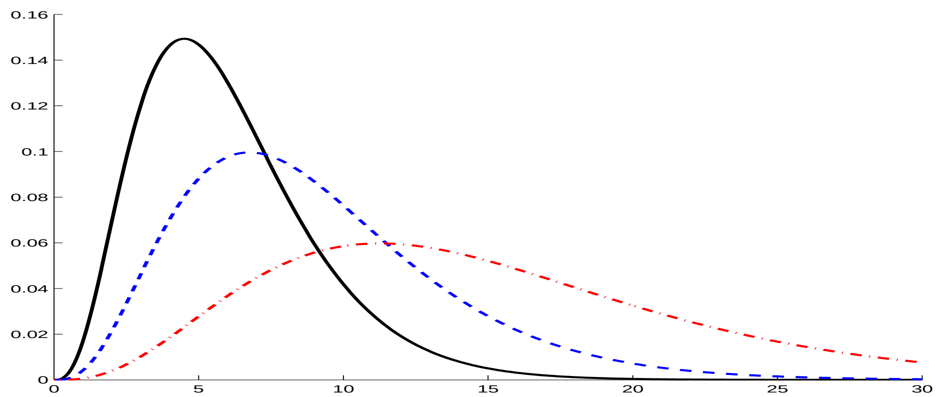
[31] In several macro applications, including previous drafts of this paper, the sampling procedure is described in this way except that the step $\vartheta|\tilde{\sigma}_{1:T}, \varsigma_{1:T}, y_{1:T}$ is mistakenly replaced with $\vartheta|\tilde{\sigma}_{1:T}, y_{1:T}$.

an inverse Gamma proposal distribution, and is then accepted or rejected in a Metropolis Hastings step.[32]

Note that step (2-1) and (2) in the KSC and JPR samplers, respectively, are identical. Section 2.1.1 describes this step in detail.

A.4 Priors on Degrees of Freedom

Figure A.1: Priors on degrees of freedom of Student's t distribution



Notes: Prior density for $\underline{\lambda} = 6$ (solid), 9 (dashed), and 15 (dash-and-dotted). All priors have $\underline{\nu} = 4$ degrees of freedom.

A.5 Marginal likelihood

The marginal likelihood is the marginal probability of the observed data, and is computed as the integral of (12) with respect to the unobserved parameters and latent variables:

$$
\begin{aligned}
p(y_{1:T}) &= \int p(y_{1:T}|s_{1:T},\theta)p(s_{1:T}|\varepsilon_{1:T},\theta)p(\varepsilon_{1:T}|\tilde{h}_{1:T},\tilde{\sigma}_{1:T},\theta) \\
&\qquad p(\tilde{h}_{1:T}|\lambda_{1:\bar{q}})p(\tilde{\sigma}_{1:T}|\omega^2_{1:\bar{q}})p(\lambda_{1:\bar{q}})p(\omega^2_{1:\bar{q}})p(\theta) \\
&\qquad d(s_{1:T},\varepsilon_{1:T},\tilde{h}_{1:T},\tilde{\sigma}_{1:T},\lambda_{1:\bar{q}},\rho_{1:\bar{q}},\omega^2_{1:\bar{q}},\theta), \qquad (46)\\
&= \int p(y_{1:T}|\tilde{h}_{1:T},\tilde{\sigma}_{1:T},\theta)p(\tilde{h}_{1:T}|\lambda_{1:\bar{q}})p(\tilde{\sigma}_{1:T}|\omega^2_{1:\bar{q}}) \\
&\qquad p(\lambda_{1:\bar{q}})p(\omega^2_{1:\bar{q}})p(\theta)d(\tilde{h}_{1:T},\tilde{\sigma}_{1:T},\lambda_{1:\bar{q}},\rho_{1:\bar{q}},\omega^2_{1:\bar{q}},\theta)
\end{aligned}
$$

[32]As noted in Jacquier et al. (1994), the posterior $\tilde{\sigma}_t|\tilde{\sigma}_{-t},\vartheta,y_{1:T}$ can also be easily sampled using a log-normal density and then applying a Metropolis Hastings step. However, JPR warn that the tails of the log-normal distribution may not be thick enough for good sampling. In line with these results, our experiments with a log-normal proposal produced largely similar results, but substantially worse convergence properties, using the criteria of Section A.8.

where the quantity

$$p(y_{1:T}|\tilde{h}_{1:T}, \tilde{\sigma}_{1:T}, \theta) = \int p(y_{1:T}|s_{1:T}, \theta)p(s_{1:T}|\varepsilon_{1:T}, \theta) \\ p(\varepsilon_{1:T}|\tilde{h}_{1:T}, \tilde{\sigma}_{1:T}, \theta) \cdot d(s_{1:T}, \varepsilon_{1:T})$$

is computed at step 1a of the Gibb-sampler described above.

We obtain the marginal likelihood using Geweke (1999)'s modified harmonic mean method. If $f(\theta, \tilde{h}_{1:T}, \tilde{\sigma}_{1:T}, \lambda_{1:\bar{q}}, \rho_{1:\bar{q}}, \omega^2_{1:\bar{q}})$ is any distribution with support contained in the support of the posterior density such that

$$\int f(\theta, \tilde{h}_{1:T}, \tilde{\sigma}_{1:T}, \lambda_{1:\bar{q}}, \rho_{1:\bar{q}}, \omega^2_{1:\bar{q}}) \cdot d(\theta, \tilde{h}_{1:T}, \tilde{\sigma}_{1:T}, \lambda_{1:\bar{q}}, \rho_{1:\bar{q}}, \omega^2_{1:\bar{q}}) = 1,$$

it follows from the definition of the posterior density that:

$$\frac{1}{p(y_{1:T})} = \int \frac{f(\theta, \tilde{h}_{1:T}, \tilde{\sigma}_{1:T}, \lambda_{1:\bar{q}}, \rho_{1:\bar{q}}, \omega^2_{1:\bar{q}})}{p(y_{1:T}|\tilde{h}_{1:T}, \tilde{\sigma}_{1:T}, \theta)p(\tilde{h}_{1:T}|\lambda_{1:\bar{q}})p(\tilde{\sigma}_{1:T}|\omega^2_{1:\bar{q}})p(\lambda_{1:\bar{q}})p(\omega^2_{1:\bar{q}})p(\theta)} \\ p(\theta, \tilde{h}_{1:T}, \tilde{\sigma}_{1:T}, \lambda_{1:\bar{q}}, \rho_{1:\bar{q}}, \omega^2_{1:\bar{q}}|y_{1:T}) \cdot d(\theta, \tilde{h}_{1:T}, \tilde{\sigma}_{1:T}, \lambda_{1:\bar{q}}, \rho_{1:\bar{q}}, \omega^2_{1:\bar{q}})$$

We follow JP in choosing

$$f(\theta, \tilde{h}_{1:T}) = f(\theta) \cdot p(\tilde{h}_{1:T}|\lambda_{1:\bar{q}})p(\tilde{\sigma}_{1:T}|\omega^2_{1:\bar{q}})p(\lambda_{1:\bar{q}})p(\omega^2_{1:\bar{q}}), \tag{47}$$

where $f(\theta)$ is a truncate multivariate distribution as proposed by Geweke (1999). Hence we approximate the marginal likelihood as:

$$\hat{p}(y_{1:T}) = \left[\frac{1}{n_{sim}} \sum_{j=1}^{n_{sim}} \frac{f(\theta^j)}{p(y_{1:T}|\tilde{h}^j_{1:T}, \tilde{\sigma}^j_{1:T}, \theta^j)p(\theta^j)} \right]^{-1} \tag{48}$$

where θ^j, $\tilde{h}^j_{1:T}$, and $\tilde{\sigma}^j_{1:T}$ are draws from the posterior distribution, and n_{sim} is the total number of draws. We are aware of the problems with (47), namely that it does not ensure that the random variable

$$\frac{f(\theta, \tilde{h}_{1:T}, \tilde{\sigma}_{1:T}, \lambda_{1:\bar{q}}, \rho_{1:\bar{q}}, \omega^2_{1:\bar{q}})}{p(y_{1:T}|\tilde{h}_{1:T}, \tilde{\sigma}_{1:T}, \theta)p(\tilde{h}_{1:T}|\lambda_{1:\bar{q}})p(\tilde{\sigma}_{1:T}|\omega^2_{1:\bar{q}})p(\lambda_{1:\bar{q}})p(\omega^2_{1:\bar{q}})p(\theta)}$$

has finite variance. Nonetheless, like JP we found that this method delivers very similar results across different chains.

A.6 Parameter Estimates

Does accounting for Student's t shocks and/or stochastic volatility affect the posterior distributions for the DSGE model parameter estimates? JP find that the answer is generally no as far as stochastic volatility is concerned. In our application we broadly reach similar conclusions. Table A.2 shows the posterior means for the parameters estimated in the following four cases: 1) Gaussian shocks and constant volatility (Baseline), 2) Gaussian shocks with stochastic volatility (SV), 3) Student's t shocks (St-t), and 4) Student's t shocks with stochastic volatility (St-t+SV). For reference, we also report the prior mean and standard deviation. We find that the parameter capturing investment adjustment costs (S'') is lower in the baseline specifications relative to the alternatives. Interestingly, JP also find that this parameter is sensitive to changing the specification of the shock distribution, in spite of using a slightly different model and a different sample. Unlike JP, we find that other parameters are also sensitive to the specification of the shock distribution. Namely, we also find that the labor disutility is somewhat more convex when we depart from Gaussianity. We find that the price rigidities parameter (ζ_p) has a higher posterior mean when we account for fat-tails than when we do not (it is about 0.73 in the Gaussian case and 0.85 in the case with both fat tails and stochastic volatility). Additionally, the estimates of the persistency of the shocks are also influenced by the inclusion of stochastic volatility and/or fat tails. Finally, Table A.25 compares the posterior means of the DSGE parameters under the various specifications for the full sample and the sample ending in 2004Q4. The posterior estimates appear to change with the sample for all specifications, hence it is not clear that specifications with SV or TD provide more "robust" parameters estimates with respect to changes in the sample. Admittedly, this issue deserves a more detailed assessment.

A.7 Posterior estimates of the shocks ($\varepsilon_{q,t}$) , stochastic volatilities ($\tilde{\sigma}_t$), Student's t scale component ($\tilde{h}_t$), "tamed" shocks (η_t), and Stochastic Volatility Innovation Variance ω_q^2

As discussed in Section 2, our model makes a strong assumption: we assume that changes in volatility are either very persistent or i.i.d. (Student's t). It is worth looking at, and analyzing, the posterior estimates of the Student's t scale components $\tilde{h}_{q,t}^{-1/2}$ and the "tamed" shocks $\eta_{q,t}$ to assess whether these are indeed i.i.d., as they ought to be, or whether there is still residual autocorrelation. Figures A.5 and A.6 in appendix A show precisely these quantities (the $\eta_{q,t}$ are in absolute value) for the SVTD($\underline{\lambda} = 6$) specification. In addition, tables A.13 and A.14 show the posterior mean of autocorrelation of the "raw" shocks ($\varepsilon_{q,t}$)

and the "tamed" shocks ($\eta_{q,t}$), respectively, across different specifications. While the autocorrelation of the "raw" shocks ($\varepsilon_{q,t}$) is non-negligible (and often higher for the Student's t case) the autocorrelation of the $\eta_{q,t}$s is always smaller in the SVTD specification, and often substantially so. In addition, the autocorrelation of the $\eta_{q,t}$s for the specification with SV only is always larger than in the SVTD specification for those shocks where the autocorrelation is non-negligible, such as the price markup (λ_f) and the policy (r^m) shocks.

Another important assumption is that both the $\eta_{q,t}$ and the $\tilde{h}_{q,t}$ are uncorrelated across different shocks q. Table A.15 shows the cross-correlation in the "tamed" shocks ($\eta_{q,t}$). The table shows that the cross-correlations are sometimes quite large for the Gaussian and SV case (e.g., up to .47 and .38, respectively, for policy r^m and discount rate b shocks) but is generally much smaller for the SVTD specification (at most .18). One may be concerned that with Student's t shocks the auto/cross correlations have migrated to the $\tilde{h}^{-1/2}$. Tables A.16 and A.17 suggest that this is not the case: all autocorrelations and cross-correlations are very small, less than .035.

Finally, figure A.7 shows the posterior estimates of the shocks $\varepsilon_{q,t}$ (in absolute value) and the shock volatilties $\sigma_{q,t}$ in the SV and SVTD specifications. The figure shows that the time series of $\sigma_{q,t}$ broadly reflects the time variation in the volatility of the shocks, and how allowing for fat tails affects the estimates of $\sigma_{q,t}$. Table A.3 shows the posterior of the SV innovation variance ω_q^2. One should bear in mind that the effect of SV shocks on $\sigma_{q,t}$ depends on the size of the non-time varying components σ_q, which is different across specifications (see Table A.2). Therefore ω_q^2 is sometimes smaller in the SV than the SVTD specification, but this is often because the corresponding estimate of σ_q is larger, and hence movements in $\sigma_{q,t}$ may well be larger.

A.8 Computational Issues and Convergence

Our results are based on 4 chains, each beginning from a different starting point, with 220,000 draws each, of which we discard the first 20,000 draws. The computational cost of using time-variation in volatility is substantial but not overwhelming. In our experiments, we found that, relative to the baseline Gaussian model, the TD, SV and SVTD estimations took roughly 2-4 times as long to sample the same number of draws. The TD, SV, and SVTD estimations all took roughly the same amount of time. The reason for this is that the main computational cost is related to drawing the disturbances on each iteration of the

Gibbs sampler (which is not necessary in a Gaussian model) rather than the drawing of the time-varying volatilities or the volatility parameters. For this (expensive) step of drawing the disturbances, we recommend the simulation smoother of Durbin and Koopman (2002), which we have found to be highly efficient relative to alternative methods.

We provide a formal assessment of convergence in Tables A.5 through A.12 of appendix A. We present convergence results for our main specification (SVTD($\bar{\lambda} = 6$)). The same convergence results are available for all the samples and sub-samples and all the different specifications. We use four metrics to assess convergence, aside from plots of the evolution of the MCMC draws in each chain and comparing histograms across chains for each parameter. First, the R statistic of Gelman and Rubin (1992), which compares the variance of each parameter estimate between and within chains and estimates the factor by which these could be reduced by continuing to take draws. This statistic is always larger or equal than one, and a cut-off of 1.01 is often used. Second, the number of effective draws in each chain for each parameter, which corrects for the serial correlation across draws following Geweke et al. (1992). Third, the number of effective draws in total, which combines the previous two corrections applied to the mixed simulations from the four chains (Gelman et al. (2004), page 298). Finally, we show the separated partial means test of Geweke et al. (1992) in which few rejections implies being closer to convergence.

We focus on showing convergence for the objects of interest in this paper: namely the value of the posterior, estimates of the degrees of freedom λ of the Student's t distribution, the variance of SV innovations, and the ratios of pre/post Great Moderation volatility. Overall, we were very satisfied with convergence for our most important specifications. As shown in the tables of Section A.9.2, the R-squared statistic for the posterior and for the parameters governing the SV and TD components all exhibit low R statistics, high numbers of effective observations, and few rejections of the separated partial means test. Convergence for the DSGE parameters θ was also generally quite good, although some parameters have only a few hundred effective draws. We found the convergence properties of our alternative specifications to be satisfactory. All convergence results are available upon request. We found that the convergence speed for our main SVTD specification and the baseline Gaussian specification were similar, as measured by the number of effective draws out of samples of the same size.

We were frequently able to improve the convergence properties of our samples by rerunning the estimation. In particular, using the previous run's realized covariance matrix of the θ parameters as the covariance of our proposal density for θ often yielded much better convergence properties.

A.9 Additional Results for Baseline Estimation

A.9.1 Parameters and Variance Decomposition

Table A.1: Priors for the Medium-Scale Model

	Density	Mean	St. Dev.		Density	Mean	St. Dev.
Policy Parameters							
ψ_1	Normal	1.50	0.25	ρ_R	Beta	0.75	0.10
ψ_2	Normal	0.12	0.05	ρ_{r^m}	Beta	0.50	0.20
ψ_3	Normal	0.12	0.05	σ_{r^m}	InvG	0.10	2.00
Nominal Rigidities Parameters							
ζ_p	Beta	0.50	0.10	ζ_w	Beta	0.50	0.10
Other "Endogenous Propagation and Steady State" Parameters							
α	Normal	0.30	0.05	π^*	Gamma	0.62	0.10
Φ	Normal	1.25	0.12	γ	Normal	0.40	0.10
h	Beta	0.70	0.10	S''	Normal	4.00	1.50
ν_l	Normal	2.00	0.75	σ_c	Normal	1.50	0.37
ι_p	Beta	0.50	0.15	ι_w	Beta	0.50	0.15
r_*	Gamma	0.25	0.10	ψ	Beta	0.50	0.15
ρs, σs, and ηs							
ρ_z	Beta	0.50	0.20	σ_z	InvG	0.10	2.00
ρ_b	Beta	0.50	0.20	σ_b	InvG	0.10	2.00
ρ_{λ_f}	Beta	0.50	0.20	σ_{λ_f}	InvG	0.10	2.00
ρ_{λ_w}	Beta	0.50	0.20	σ_{λ_w}	InvG	0.10	2.00
ρ_μ	Beta	0.50	0.20	σ_μ	InvG	0.10	2.00
ρ_g	Beta	0.50	0.20	σ_g	InvG	0.10	2.00
η_{λ_f}	Beta	0.50	0.20	η_{λ_w}	Beta	0.50	0.20
η_{gz}	Beta	0.50	0.20				

Notes: Note that $\beta = (1/(1 + r_*/100))$. The following parameters are fixed in Smets and Wouters (2007): $\delta = 0.025$, $g_* = 0.18$, $\lambda_w = 1.50$, $\varepsilon_w = 10.0$, and $\varepsilon_p = 10$. The columns "Mean" and "St. Dev." list the means and the standard deviations for Beta, Gamma, and Normal distributions, and the values s and ν for the Inverse Gamma (InvG) distribution, where $p_{\mathcal{IG}}(\sigma|\nu, s) \propto \sigma^{-\nu-1}e^{-\nu s^2/2\sigma^2}$. The effective prior is truncated at the boundary of the determinacy region. The prior for $\bar{l}$ is $\mathcal{N}(-45, 5^2)$.

Table A.2: Posterior Means of the DSGE Model Parameters

	Prior Mean	Prior SD	Baseline	SV	St-t	St-t+SV
α	0.300	0.050	0.150	0.134	0.150	0.135
ζ_p	0.500	0.100	0.734	0.780	0.808	0.846
ι_p	0.500	0.150	0.315	0.344	0.383	0.286
Φ	1.250	0.120	1.580	1.518	1.575	1.551
S''	4.000	1.500	4.686	5.013	5.070	5.651
h	0.700	0.100	0.611	0.609	0.582	0.571
ψ	0.500	0.150	0.714	0.734	0.670	0.666
ν_l	2.000	0.750	2.088	2.212	2.300	2.476
ζ_w	0.500	0.100	0.803	0.826	0.830	0.843
ι_w	0.500	0.150	0.541	0.547	0.495	0.511
β	0.250	0.100	0.206	0.184	0.202	0.175
ψ_1	1.500	0.250	1.953	1.866	1.820	1.884
ψ_2	0.120	0.050	0.083	0.073	0.115	0.116
ψ_3	0.120	0.050	0.245	0.217	0.213	0.184
π^*	0.620	0.100	0.683	0.719	0.706	0.808
σ_c	1.500	0.370	1.236	1.109	1.248	1.274
ρ	0.750	0.100	0.835	0.854	0.875	0.875
γ	0.400	0.100	0.306	0.321	0.356	0.389
$\bar{L}$	-45.00	5.000	-44.17	-46.67	-43.38	-44.73
ρ_g	0.500	0.200	0.977	0.977	0.982	0.988
ρ_b	0.500	0.200	0.758	0.845	0.844	0.852
ρ_μ	0.500	0.200	0.748	0.753	0.791	0.806
ρ_z	0.500	0.200	0.994	0.991	0.987	0.981
ρ_{λ_f}	0.500	0.200	0.791	0.797	0.811	0.830
ρ_{λ_w}	0.500	0.200	0.981	0.952	0.962	0.923
ρ_{rm}	0.500	0.200	0.154	0.219	0.219	0.227
σ_g	0.100	2.000	2.892	3.169	2.387	2.665
σ_b	0.100	2.000	0.125	0.122	0.072	0.100
σ_μ	0.100	2.000	0.430	0.454	0.325	0.300
σ_z	0.100	2.000	0.493	0.869	0.362	0.473
σ_{λ_f}	0.100	2.000	0.164	0.191	0.163	0.127
σ_{λ_w}	0.100	2.000	0.281	0.203	0.213	0.151
σ_{rm}	0.100	2.000	0.228	0.243	0.133	0.095
η_{gz}	0.500	0.200	0.787	0.775	0.786	0.765
η_{λ_f}	0.500	0.200	0.670	0.749	0.815	0.734
η_{λ_w}	0.500	0.200	0.948	0.914	0.924	0.865

Notes: We use a prior mean of 6 degrees of freedom for the Student's t distributed component. The stochastic volatility component assumes a prior mean for the size of the shocks to volatility of $(0.01)^2$.

Figure A.2: Prior on Innovation Variance (ω^2) for Stochastic Volatility

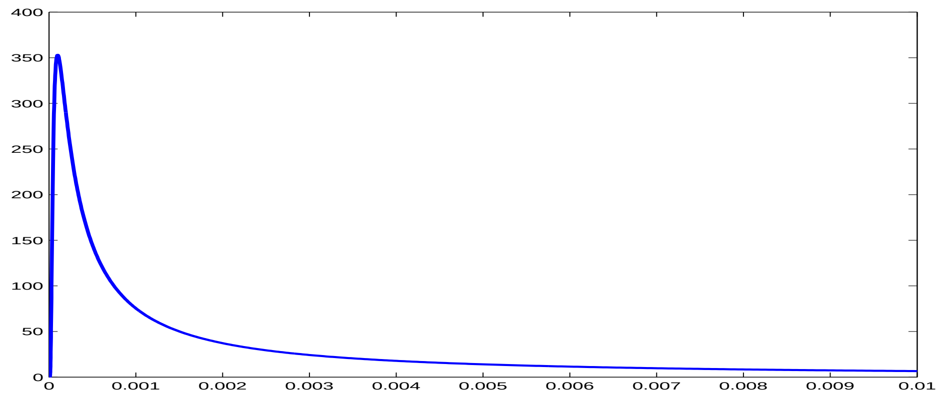


Table A.3: Posterior of the Stochastic Volatility Innovation Variance

	Without Student's t	*With Student's t*
g	0.001	0.007
	(0.000,0.002)	(0.000,0.015)
b	0.003	0.005
	(0.000,0.006)	(0.000,0.0012)
μ	0.000	0.002
	(0.000,0.001)	(0.000,0.005)
z	0.002	0.003
	(0.000,0.004)	(0.000,0.007)
λ_f	0.001	0.008
	(0.000,0.003)	(0.001,0.016)
λ_w	0.001	0.002
	(0.000,0.002)	(0.002,0.005)
r^m	0.006	0.022
	(0.000,0.011)	(0.005,0.039)

Notes: Numbers shown for the posterior mean and the 90% intervals of the stochastic volatility innovation variance.

Table A.4: Variance Decomposition for Real GDP Growth

Gaussian Shocks

	g	b	μ	z	λ_f	λ_w	r^m
Without Stochastic Volatility							
	0.225	0.354	0.095	0.140	0.041	0.036	0.109
With Stochastic Volatility							
σ_{1964}	0.162	0.359	0.062	0.252	0.031	0.012	0. 123
σ_{1981}	0.160	0.438	0.052	0.075	0.027	0.016	0. 233
σ_{1994}	0.240	0.306	0.120	0.136	0.052	0.057	0. 089
σ_{2007}	0.189	0.312	0.106	0.156	0.062	0.068	0. 106
σ_{2011}	0.175	0.318	0.100	0.163	0.062	0.061	0. 121

Student's t Shocks

	g	b	μ	z	λ_f	λ_w	r^m
Without Stochastic Volatility							
	0.184	0.352	0.083	0.124	0.036	0.020	0.199
With Stochastic Volatility							
σ_{1964}	0.170	0.417	0.082	0.207	0.034	0.016	0. 073
σ_{1981}	0.205	0.350	0.075	0.091	0.032	0.021	0. 225
σ_{1994}	0.178	0.394	0.109	0.142	0.038	0.045	0. 094
σ_{2007}	0.163	0.361	0.104	0.155	0.044	0.054	0. 118
σ_{2011}	0.168	0.359	0.105	0.138	0.048	0.051	0. 132

Notes: The tables show the relative contribution of the different shocks to the unconditional variance of real GDP. In the case with stochastic volatility we evaluate this contribution at different points in time assuming that volatility will be fixed at that period's level from then on: 1964 (beginning of sample), 1981 (peak of the high volatility period), 1994 (great moderation), 2007 (pre-great recession) and 2011 (end of sample).

A.9.2 Convergence Tables

Table A.5: R Statistic and Number of Effective Draws: Posterior

	R	mn^{eff}	$n^{eff}(1)$	$n^{eff}(2)$	$n^{eff}(3)$	$n^{eff}(4)$
post	1.0001	16393	4871	4897	4071	4400

Table A.6: Separated Partial Means Test: Posterior

	$SPM_4(1)$	$SPM_4(2)$	$SPM_4(3)$	$SPM_4(4)$
post	3.76	1.61	2.02	2.37

The null hypothesis of the SPM test is that the mean in two separate subsamples is the same. * indicates p-value less than 5%. ** indicates p-value less than 1%.

Table A.7: R Statistic and Number of Effective Draws: Student's t Degrees of Freedom (λ)

	R	mn^{eff}	$n^{eff}(1)$	$n^{eff}(2)$	$n^{eff}(3)$	$n^{eff}(4)$
g	1.0001	28090	5781	7019	5894	7309
b	1.0001	16072	4118	2268	3113	1490
μ	1.0001	32383	4703	4658	5683	4388
z	1.0002	11328	1981	2657	2859	2550
λ_f	1.0001	19064	6741	6382	4886	4382
λ_w	1.0001	16329	9489	8524	7566	3714
r^m	1.0002	7946	3956	3716	4365	3000

Table A.8: Separated Partial Means Test: Student's t Degrees of Freedom (λ)

	$SPM_4(1)$	$SPM_4(2)$	$SPM_4(3)$	$SPM_4(4)$
g	3.12	3.99	2.59	2.99
b	2.01	1.50	0.72	6.32
μ	1.55	3.48	1.07	0.48
z	7.75	4.58	0.50	8.56 *
λ_f	0.06	0.21	6.16	2.31
λ_w	0.65	0.82	3.89	3.86
r^m	3.98	2.09	1.44	2.72

The null hypothesis of the SPM test is that the mean in two separate subsamples is the same. * indicates p-value less than 5%. ** indicates p-value less than 1%.

Table A.9: R Statistic and Number of Effective Draws: SV Innovation Variance

	R	mn^{eff}	$n^{eff}(1)$	$n^{eff}(2)$	$n^{eff}(3)$	$n^{eff}(4)$
g	1.0014	1451	1038	1739	1428	1159
b	1.0001	32466	4481	7342	6195	4399
μ	1.0003	6324	4139	5848	6985	6569
z	1.0001	14141	2118	3256	2908	2533
λ_f	1.0013	1549	1936	1475	1780	769
λ_w	1.0018	1133	1794	2393	2429	348
r^m	1.0003	6221	2179	2089	3343	3020

Table A.10: Separated Partial Means Test: SV Innovation Variance

	$SPM_4(1)$	$SPM_4(2)$	$SPM_4(3)$	$SPM_4(4)$	
g	2.75	4.77	5.37	2.03	
b	0.96	1.98	4.17	1.63	
μ	3.94	1.96	2.37	3.14	
z	3.58	1.80	0.27	10.60	*
λ_f	0.23	1.95	1.00	4.40	
λ_w	1.47	4.15	3.22	4.72	
r^m	3.65	4.02	1.58	2.09	

The null hypothesis of the SPM test is that the mean in two separate subsamples is the same. * indicates p-value less than 5%. ** indicates p-value less than 1%.

Table A.11: R Statistic and Number of Effective Draws: Ratio of 1981 to 1994 Variance

	R	mn^{eff}	$n^{eff}(1)$	$n^{eff}(2)$	$n^{eff}(3)$	$n^{eff}(4)$
Output Growth	1.0002	9654	2627	6393	3794	2444
Per Capita Consumption Growth	1.0003	6734	3421	1387	5583	4921
Per Capita Investment Growth	1.0000	57827	2318	5256	9423	8376

Table A.12: Separated Partial Means Test: Ratio of 1981 to 1994 Variance

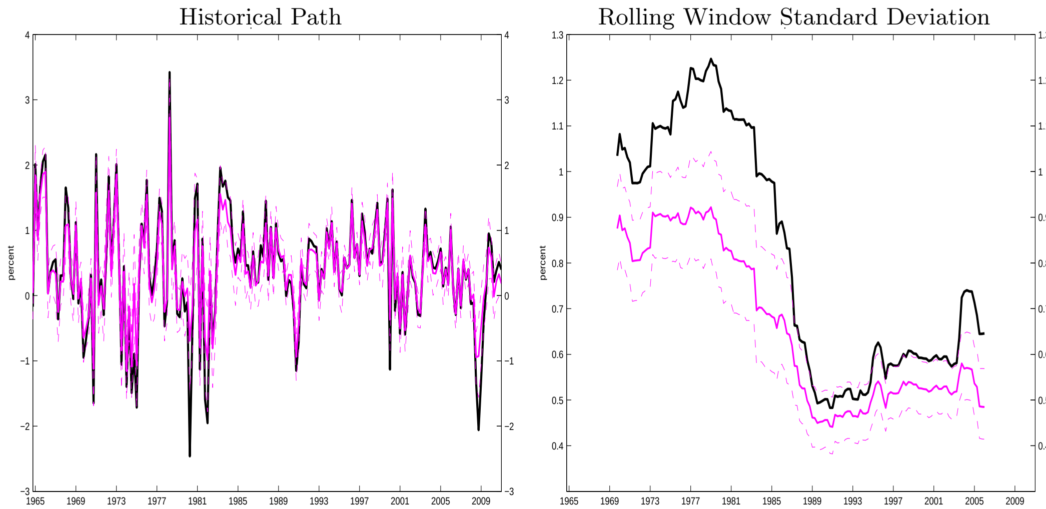
	$SPM_4(1)$	$SPM_4(2)$	$SPM_4(3)$	$SPM_4(4)$
Output Growth	2.88	1.39	3.69	0.22
Per Capita Consumption Growth	2.68	4.76	4.43	1.31
Per Capita Investment Growth	1.93	5.78	0.97	2.70

The null hypothesis of the SPM test is that the mean in two separate subsamples is the same. * indicates p-value less than 5%. ** indicates p-value less than 1%.

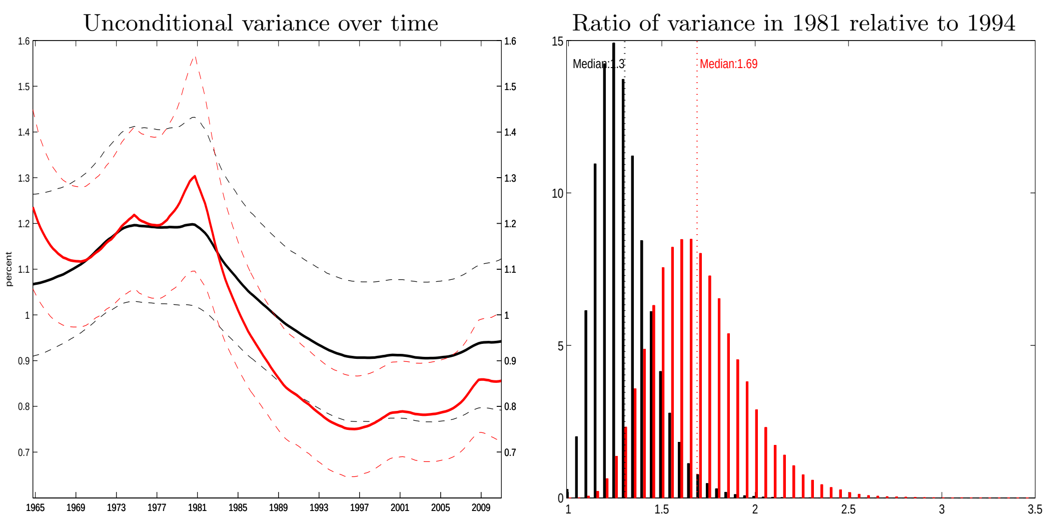
A.9.3 Robustness to the choice of $\underline{\lambda}$

Figure A.3: Results for $\underline{\lambda} = 9$

Output Growth: Counterfactual evolution with Student's t component turned off



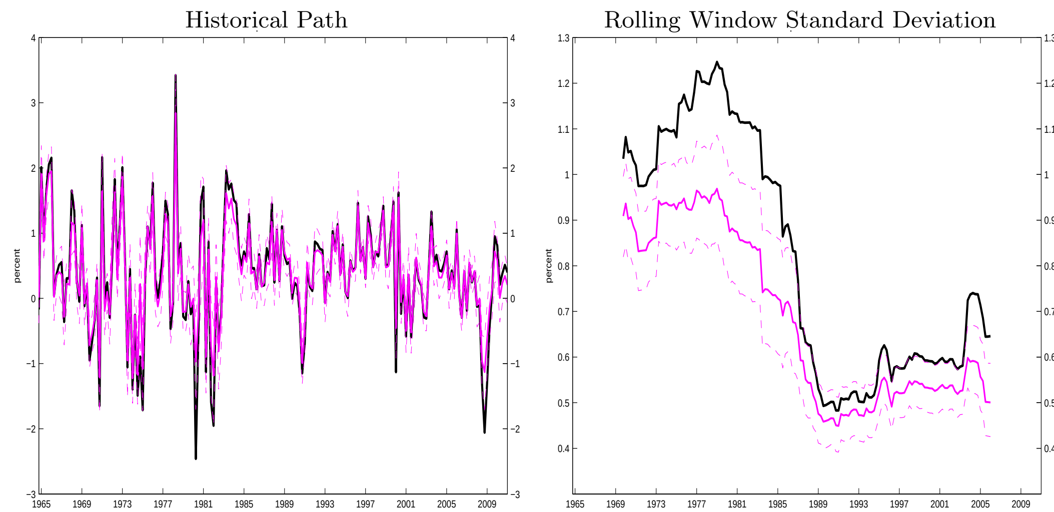
Output Growth: SV versus SV + Student's t



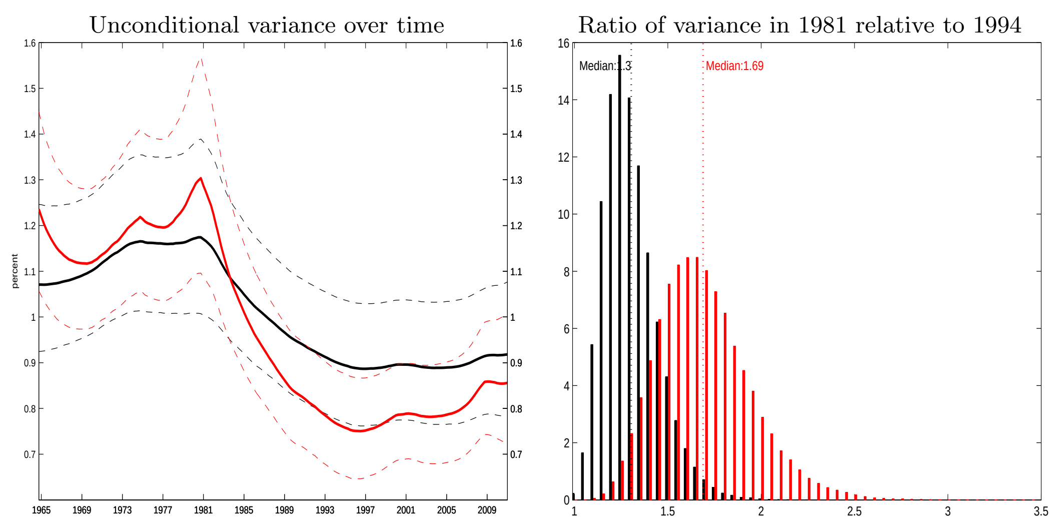
Notes: Top panels: Black lines are the historical evolution of the variable, and magenta lines are the median counterfactual evolution of the same variable if we shut down the Student-t distributed component of all shocks. The rolling window standard deviation uses 20 quarters before and 20 quarters after a given quarter. Southwest panel: Black line is the unconditional standard deviation in the estimation with both stochastic volatility and Student-t components, while the red line is the unconditional variance in the estimation with stochastic volatility component only. Southeast panel: Black bars correspond to the posterior histogram of the ratio of volatility in 1981 over the variance in 1994 for the estimation with both stochastic volatility and Student-t components, while the red bars are for the estimation with with stochastic volatility component only.

Figure A.4: Results for $\underline{\lambda} = 15$

Output Growth: Counterfactual evolution with Student's t component turned off



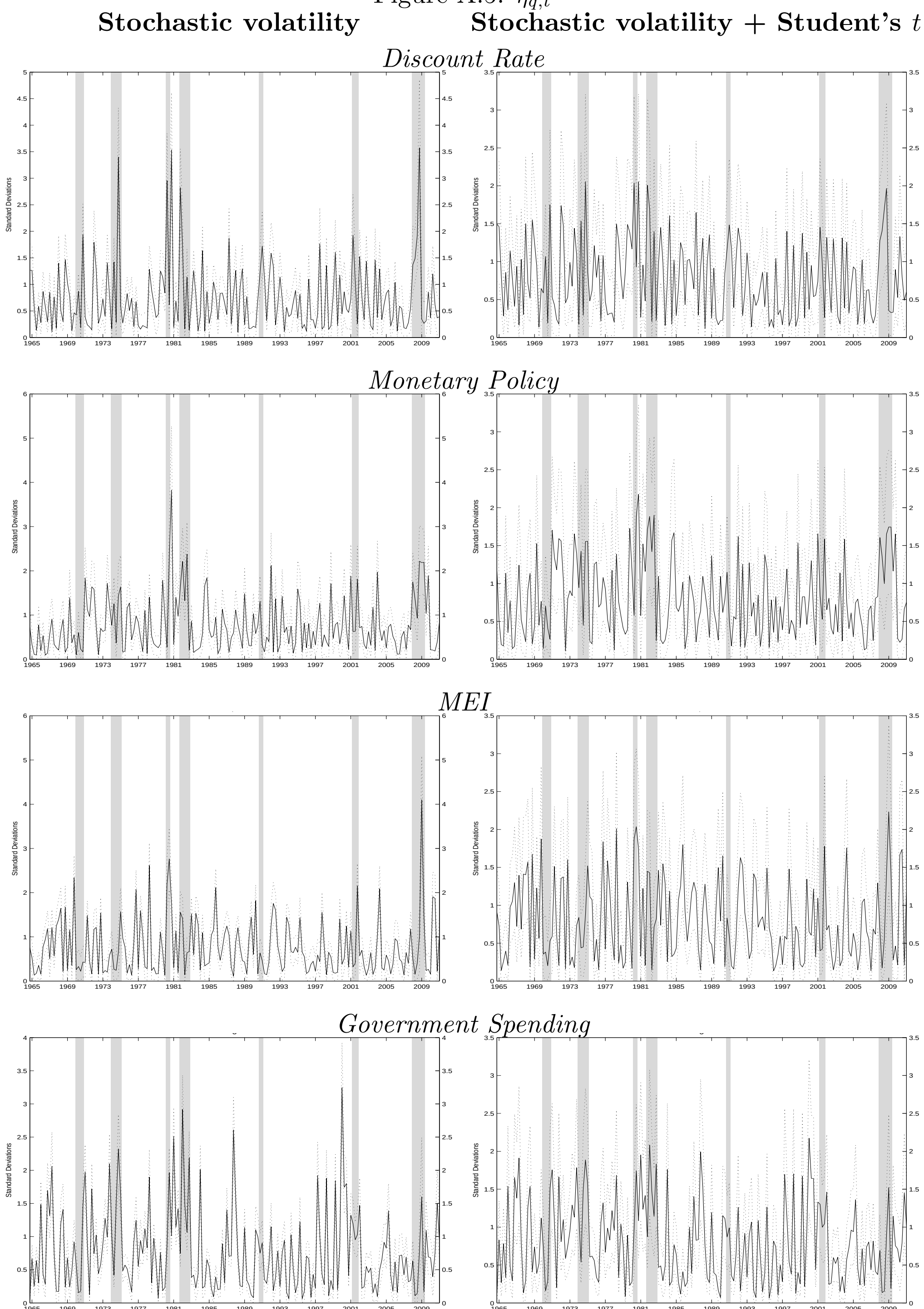
Output Growth: SV versus SV + Student's t



Notes: Top panels: Black lines are the historical evolution of the variable, and magenta lines are the median counterfactual evolution of the same variable if we shut down the Student-t distributed component of all shocks. The rolling window standard deviation uses 20 quarters before and 20 quarters after a given quarter. Southwest panel: Black line is the unconditional standard deviation in the estimation with both stochastic volatility and Student-t components, while the red line is the unconditional variance in the estimation with stochastic volatility component only. Southeast panel: Black bars correspond to the posterior histogram of the ratio of volatility in 1981 over the variance in 1994 for the estimation with both stochastic volatility and Student-t components, while the red bars are for the estimation with with stochastic volatility component only.

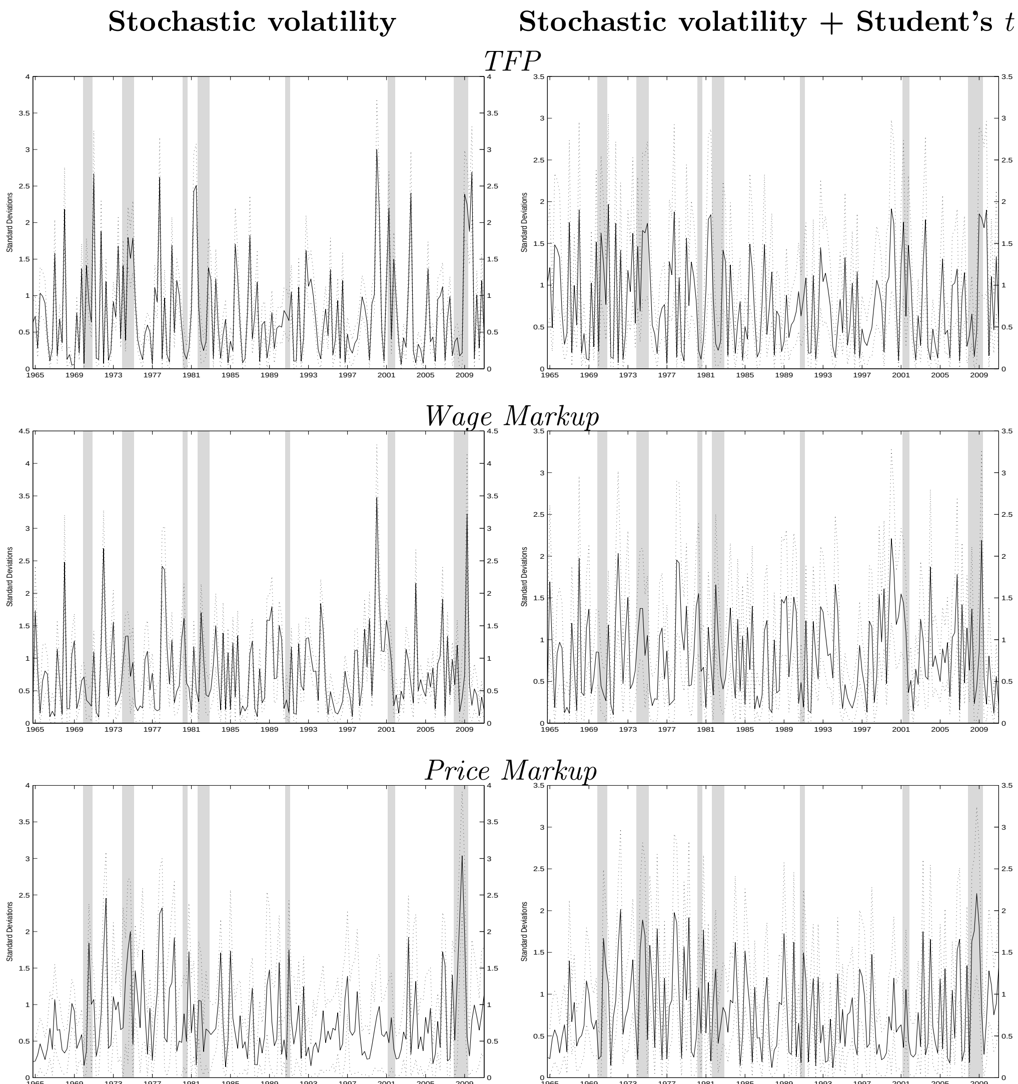
A.9.4 Posterior estimates of the shocks $(\varepsilon_{q,t})$, stochastic volatilities $(\tilde{\sigma}_t)$, Student's t scale component $(\tilde{h}_t)$, and "tamed" shocks (η_t)

Figure A.5: $\eta_{q,t}$



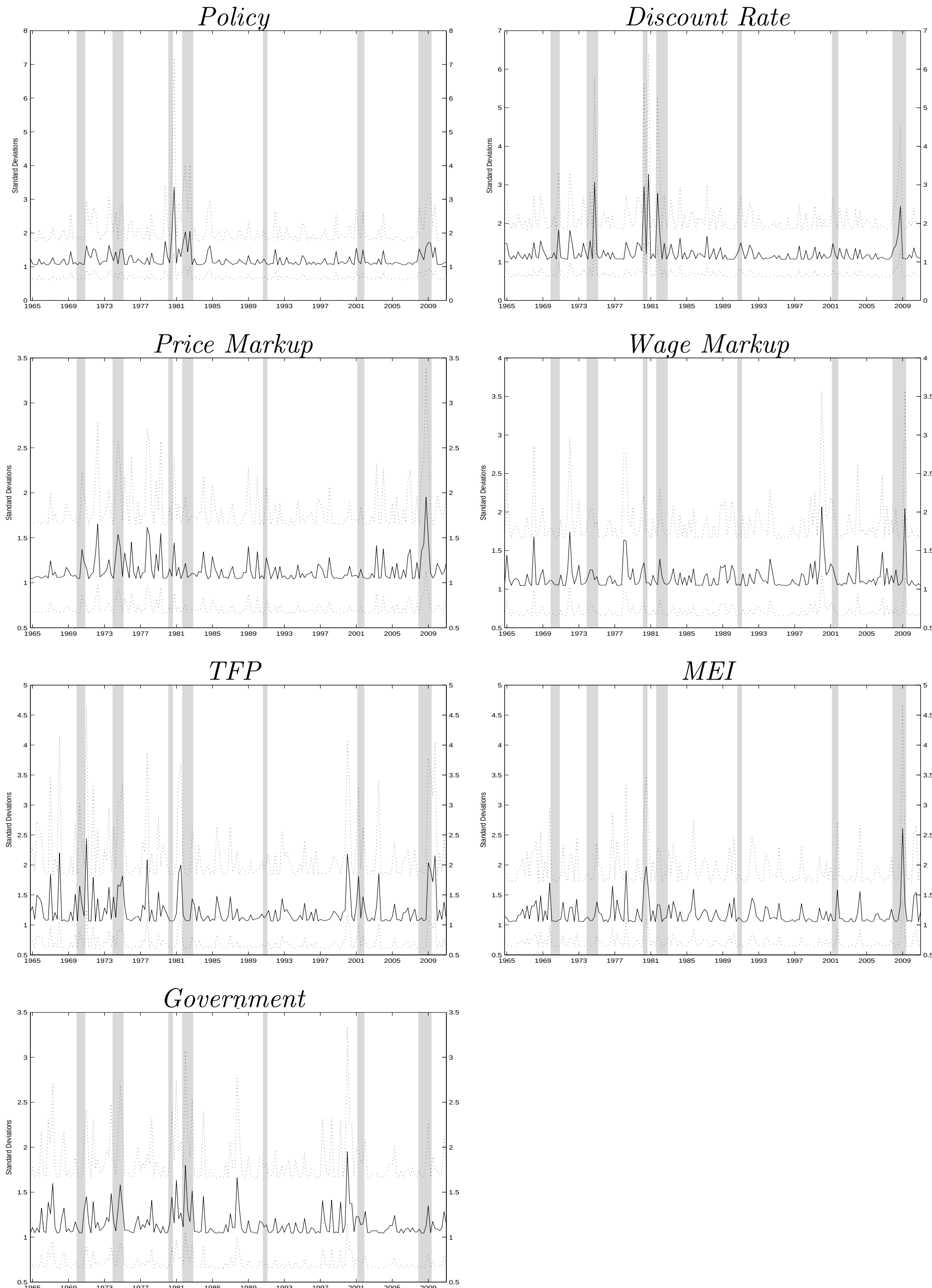
Notes: Estimation with Student's t distribution with $\underline{\lambda} = 6$. The solid line is the median, and the dashed lines are the posterior 90% bands. Black line is the absolute value of the shock, and the red line is the stochastic volatility component.

Figure A.5 — Continued



Notes: Estimation with Student’s t distribution with $\underline{\lambda} = 6$. The solid line is the median, and the dashed lines are the posterior 90% bands. Black line is the absolute value of the shock, and the red line is the stochastic volatility component.

Figure A.6: $\tilde{h}_{q,t}^{-1/2}$



Notes: Estimation with Student's t distribution with $\underline{\lambda} = 6$. The solid line is the median, and the dashed lines are the posterior 90% bands. Black line is the absolute value of the shock, and the red line is the stochastic volatility component.

Table A.13: Autocorrelation of Squared "Raw" Shocks ($\varepsilon_{q,t}$)

Spec.	g	b	μ	z	λ_f	λ_w	r^m
Gaussian	0.191	0.054	0.095	0.101	0.282	0.158	0.350
Student t	0.216	0.004	0.131	0.106	0.306	0.199	0.263
SV	0.221	0.066	0.135	0.534	0.297	0.223	0.322
SV + t	0.303	0.061	0.222	0.256	0.382	0.213	0.290

Table A.14: Autocorrelation of Squared "Tamed" Shocks ($\eta_{q,t}$)

Spec.	g	b	μ	z	λ_f	λ_w	r^m
Gaussian	0.191	0.054	0.095	0.101	0.282	0.158	0.350
Student t	0.178	0.026	0.060	0.072	0.141	0.142	0.175
SV	0.146	0.024	0.103	0.187	0.227	0.149	0.210
SV + t	0.143	0.027	0.074	0.083	0.124	0.122	0.155

Table A.15: Cross Correlation of "Tamed" Shocks ($\eta_{q,t}$)

	g	b	μ	z	λ_f	λ_w	r^m
Gaussian							
g	1.000	0.193	0.130	0.289	0.080	0.179	0.255
b	0.193	1.000	0.200	-0.010	0.267	0.001	0.472
μ	0.130	0.200	1.000	0.099	0.107	0.030	0.308
z	0.289	-0.010	0.099	1.000	0.111	0.251	0.106
λ_f	0.080	0.267	0.107	0.111	1.000	0.047	0.181
λ_w	0.179	0.001	0.030	0.251	0.047	1.000	0.039
r^m	0.255	0.472	0.308	0.106	0.181	0.039	1.000
Student's t							
g	1.000	0.064	0.074	0.181	0.059	0.043	0.179
b	0.064	1.000	0.102	-0.014	0.110	0.036	0.159
μ	0.074	0.102	1.000	0.027	-0.010	0.044	0.106
z	0.181	-0.014	0.027	1.000	0.049	0.090	0.109
λ_f	0.059	0.110	-0.010	0.049	1.000	0.029	0.094
λ_w	0.043	0.036	0.044	0.090	0.029	1.000	0.040
r^m	0.179	0.159	0.106	0.109	0.094	0.040	1.000
SV							
g	1.000	0.089	0.096	0.299	0.021	0.231	0.152
b	0.089	1.000	0.091	-0.053	0.308	0.027	0.380
μ	0.096	0.091	1.000	0.110	0.047	0.068	0.251
z	0.299	-0.053	0.110	1.000	0.052	0.297	0.153
λ_f	0.021	0.308	0.047	0.052	1.000	0.075	0.162
λ_w	0.231	0.027	0.068	0.297	0.075	1.000	0.107
r^m	0.152	0.380	0.251	0.153	0.162	0.107	1.000
SV + Student's t							
g	1.000	0.044	0.054	0.176	0.028	0.077	0.154
b	0.044	1.000	0.114	-0.032	0.115	0.071	0.160
μ	0.054	0.114	1.000	0.029	0.026	0.058	0.130
z	0.176	-0.032	0.029	1.000	0.029	0.112	0.111
λ_f	0.028	0.115	0.026	0.029	1.000	0.073	0.089
λ_w	0.077	0.071	0.058	0.112	0.073	1.000	0.074
r^m	0.154	0.160	0.130	0.111	0.089	0.074	1.000

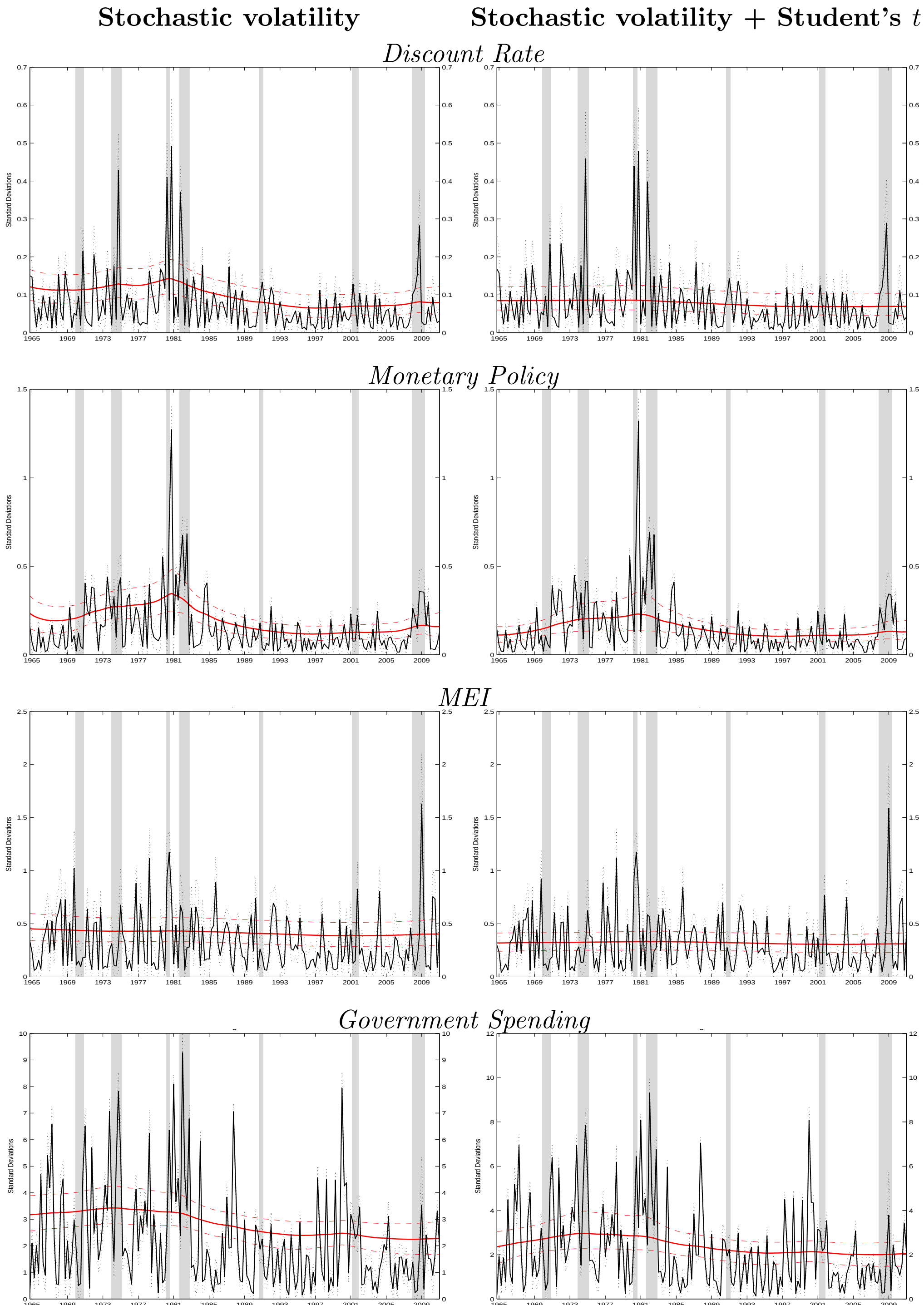
Table A.16: Autocorrelation of $\tilde{h}^{-1/2}$

Spec.	g	b	μ	z	λ_f	λ_w	r^m
No SV	0.033	0.005	0.011	0.019	0.023	0.024	0.061
SV	0.022	0.004	0.013	0.018	0.018	0.018	0.032

Table A.17: Cross Correlation of $\tilde{h}^{-1/2}$

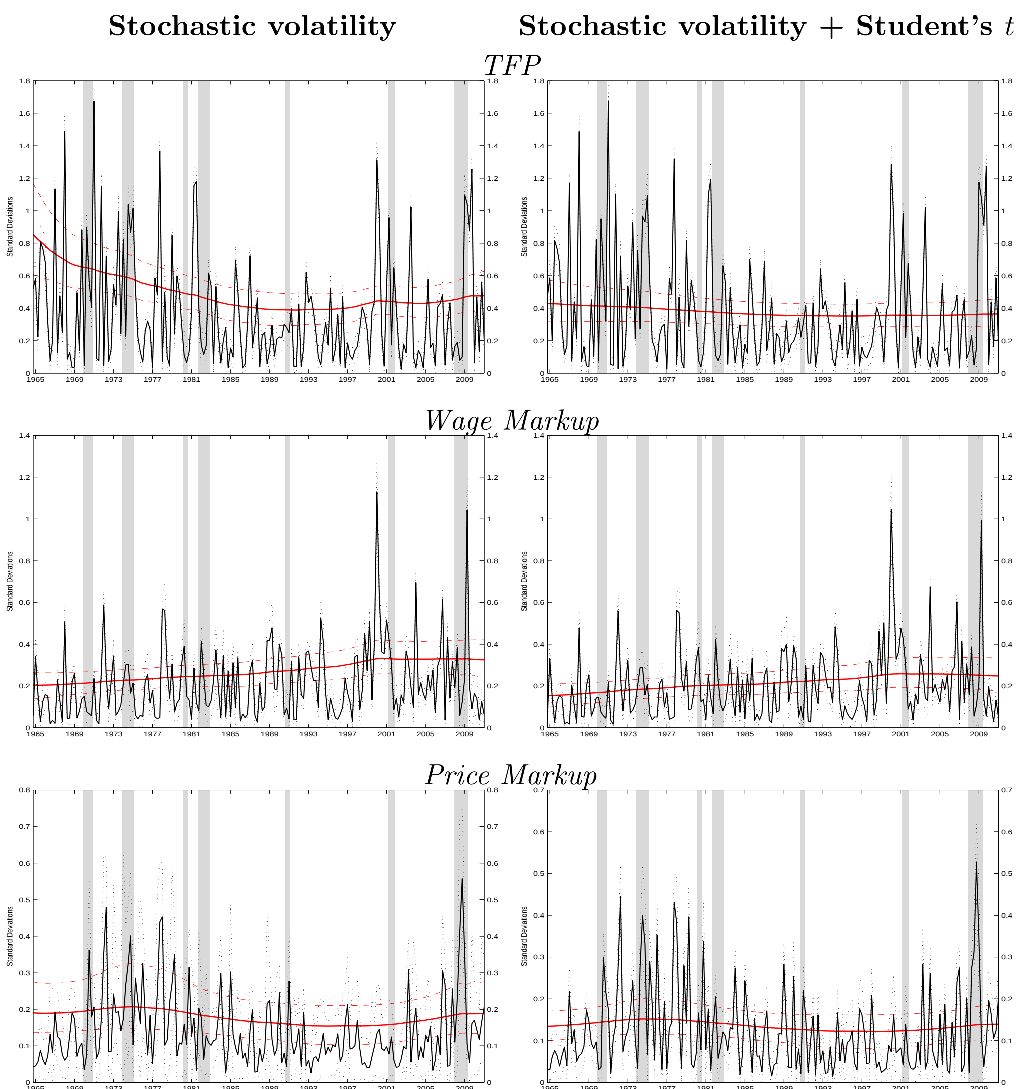
			Student t				
	g	b	μ	z	λ_f	λ_w	r^m
g	1.000	0.013	0.013	0.039	0.010	0.007	0.045
b	0.013	1.000	0.022	-0.004	0.022	0.007	0.047
μ	0.013	0.022	1.000	0.005	-0.002	0.007	0.026
z	0.039	-0.004	0.005	1.000	0.010	0.019	0.033
λ_f	0.010	0.022	-0.002	0.010	1.000	0.005	0.022
λ_w	0.007	0.007	0.007	0.019	0.005	1.000	0.009
r^m	0.045	0.047	0.026	0.033	0.022	0.009	1.000
			SV + Student t				
g	1.000	0.008	0.009	0.034	0.004	0.012	0.027
b	0.008	1.000	0.023	-0.008	0.021	0.013	0.035
μ	0.009	0.023	1.000	0.005	0.004	0.010	0.025
z	0.034	-0.008	0.005	1.000	0.004	0.021	0.024
λ_f	0.004	0.021	0.004	0.004	1.000	0.011	0.015
λ_w	0.012	0.013	0.010	0.021	0.011	1.000	0.013
r^m	0.027	0.035	0.025	0.024	0.015	0.013	1.000

Figure A.7: Shocks (absolute values) and smoothed stochastic volatility component, $\sigma_{q,t}$



Notes: Estimation with Student's t distribution with $\underline{\lambda} = 6$. The solid line is the median, and the dashed lines are the posterior 90% bands. Black line is the absolute value of the shock, and the red line is the stochastic volatility component.

Figure A.7 — Continued



Notes: Estimation with Student's t distribution with $\underline{\lambda} = 6$. The solid line is the median, and the dashed lines are the posterior 90% bands. Black line is the absolute value of the shock, and the red line is the stochastic volatility component.

A.10 Robustness to Different Assumptions and Estimation Approches for the Stochastic Volatility Component

A.10.1 JPR Version of Algorithm

Table A.18: Log-Marginal Likelihoods, JPR Algorithm

	Constant Volatility	Stochastic Volatility
Gaussian shocks		
	-1117.9	-975.2
Student's t distributed shocks		
$\underline{\lambda} = 15$	-999.8	-945.1
$\underline{\lambda} = 9$	-990.6	-936.3
$\underline{\lambda} = 6$	-975.9	-928.7

Notes: The parameter $\underline{\lambda}$ represents the prior mean for the degrees of freedom in the Student's t distribution.

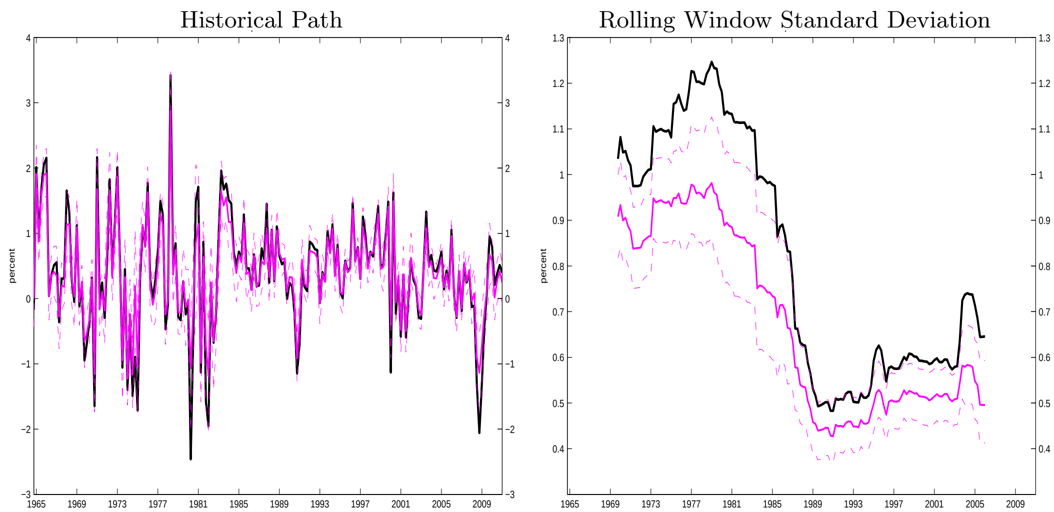
Table A.19: Posterior of the Student's t Degrees of Freedom, JPR Algorithm

	Without Stochastic Volatility			*With Stochastic Volatility*		
	$\underline{\lambda} = 15$	$\underline{\lambda} = 9$	$\underline{\lambda} = 6$	$\underline{\lambda} = 15$	$\underline{\lambda} = 9$	$\underline{\lambda} = 6$
Government (g)	10.8	7.7	6.1	14.0	9.9	7.6
	(3.5,18.4)	(3.1,12.4)	(2.8,9.4)	(4.8, 23.0)	(4.2, 15.5)	(3.7, 11.6)
Discount (b)	8.6	6.8	5.7	7.9	6.4	5.4
	(3.4,14.0)	(3.2,10.5)	(2.8,8.4)	(2.6, 13.8)	(2.7, 10.2)	(2.6, 8.0)
MEI (μ)	11.0	8.0	6.5	3.4	7.6	6.2
	(3.7,18.4)	(3.3,12.7)	(3.1,9.8)	(2.9, 17.6)	(3.1, 12.0)	(2.9, 9.3)
TFP (z)	5.3	4.5	3.9	9.9	7.1	5.6
	(2.0,8.7)	(2.0,6.9)	(2.0,5.8)	(2.9, 17.3)	(2.7, 11.5)	(2.5, 8.7)
Price Markup (λ_f)	10.5	7.5	6.1	15.3	10.6	8.2
	(3.4,17.9)	(3.1,12.0)	(2.9,9.3)	(5.6, 24.7)	(4.6, 16.5)	(4.0, 12.3)
Wage Markup (λ_w)	10.9	8.1	6.5	11.9	8.6	6.9
	(3.8,18.1)	(3.5,12.6)	(3.2,9.7)	(4.1, 19.9)	(3.6, 13.4)	(3.4,10.3)
Policy (r^m)	3.2	3.0	2.9	15.0	10.5	8.1
	(1.7,4.6)	(1.7,4.3)	(1.7,4.1)	(5.4, 24.5)	(4.5, 16.4)	(3.9, 12.2)

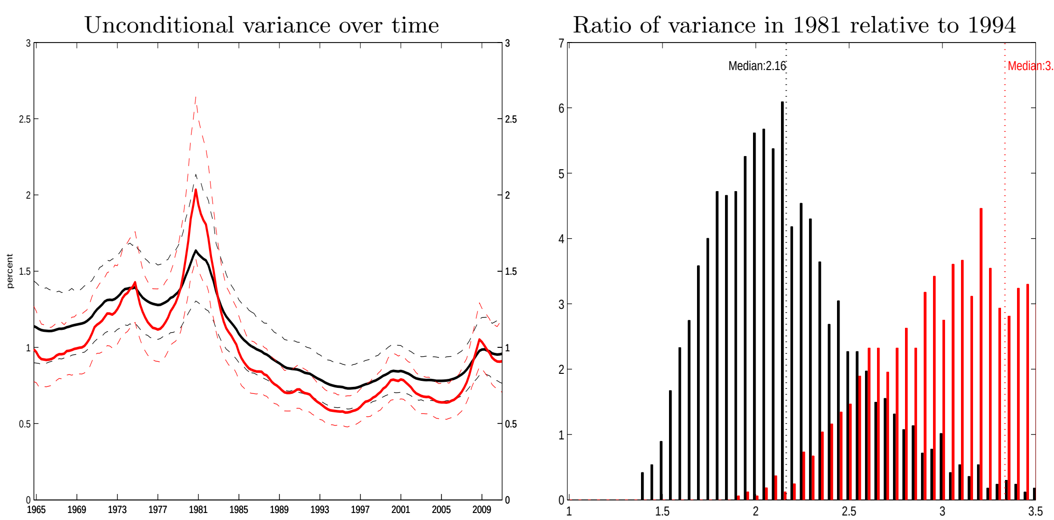
Notes: Numbers shown for the posterior mean and the 90% intervals of the degrees of freedom parameter.

Figure A.8: Results using JPR Algorithm

Output Growth: Counterfactual evolution with Student’s t component turned off



Output Growth: SV versus SV + Student’s t



Notes: Top panels: Black lines are the historical evolution of the variable, and magenta lines are the median counterfactual evolution of the same variable if we shut down the Student-t distributed component of all shocks. The rolling window standard deviation uses 20 quarters before and 20 quarters after a given quarter. Southwest panel: Black line is the unconditional standard deviation in the estimation with both stochastic volatility and Student-t components, while the red line is the unconditional variance in the estimation with stochastic volatility component only. Southeast panel: Black bars correspond to the posterior histogram of the ratio of volatility in 1981 over the variance in 1994 for the estimation with both stochastic volatility and Student-t components, while the red bars are for the estimation with with stochastic volatility component only.

A.10.2 SV-S Specification

Table A.20: Log-Marginal Likelihoods, SV-S Specification

	Constant Volatility	Stochastic Volatility
Gaussian shocks		
	-1117.9	-1100.2
Student's t distributed shocks		
$\underline{\lambda} = 6$	-975.9	-971.0

Notes: The parameter $\underline{\lambda}$ represents the prior mean for the degrees of freedom in the Student's t distribution.

Table A.21: Posterior of the Student's t Degrees of Freedom, SV-S Specification

	Without Stochastic Volatility	*With Stochastic Volatility*
	$\underline{\lambda} = 6$	$\underline{\lambda} = 6$
Government (g)	6.1 (2.8,9.4)	7.2 (3.4, 11.0)
Discount (b)	5.7 (2.8,8.4)	4.1 (2.3, 5.8)
MEI (μ)	6.5 (3.1,9.8)	5.7 (2.8, 8.6)
TFP (z)	3.9 (2.0,5.8)	4.2 (2.1, 6.4)
Price Markup (λ_f)	6.1 (2.9,9.3)	6.6 (3.2, 10.0)
Wage Markup (λ_w)	6.5 (3.2,9.7)	6.1 (3.0, 9.0)
Policy (r^m)	2.9 (1.7,4.1)	3.2 (1.7, 4.6)

Notes: Numbers shown for the posterior mean and the 90% intervals of the degrees of freedom parameter.

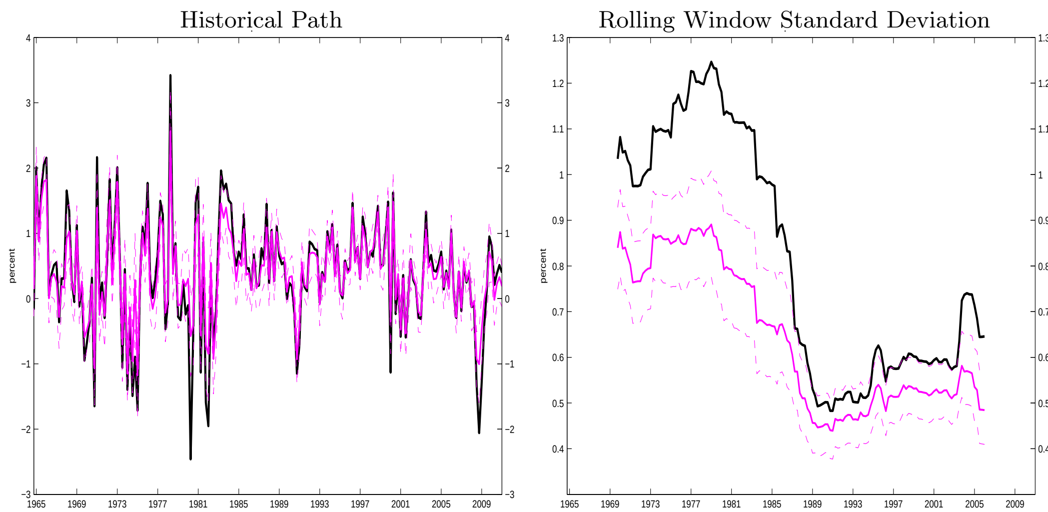
Table A.22: Posterior of SV Persistence Parameter, SV-S pecification

	Without Student t	*With Student t*
Government (g)	0.495 (0.091, 0.803)	0.879 (0.470, 1.000)
Discount (b)	0.711 (0.295, 1.000)	0.475 (0.129, 0.781)
MEI (μ)	0.472 (0.130, 0.782)	0.473 (0.133, 0.778)
TFP (z)	1.000 (0.999, 1.000)	0.473 (0.126, 0.777)
Price Markup (λ_f)	0.477 (0.132, 0.789)	0.477 (0.125, 0.785)
Wage Markup (λ_w)	0.514 (0.200, 1.000)	0.475 (0.129, 0.781)
Policy (r^m)	0.990 (0.977, 1.000)	0.518 (0.205, 1.000)

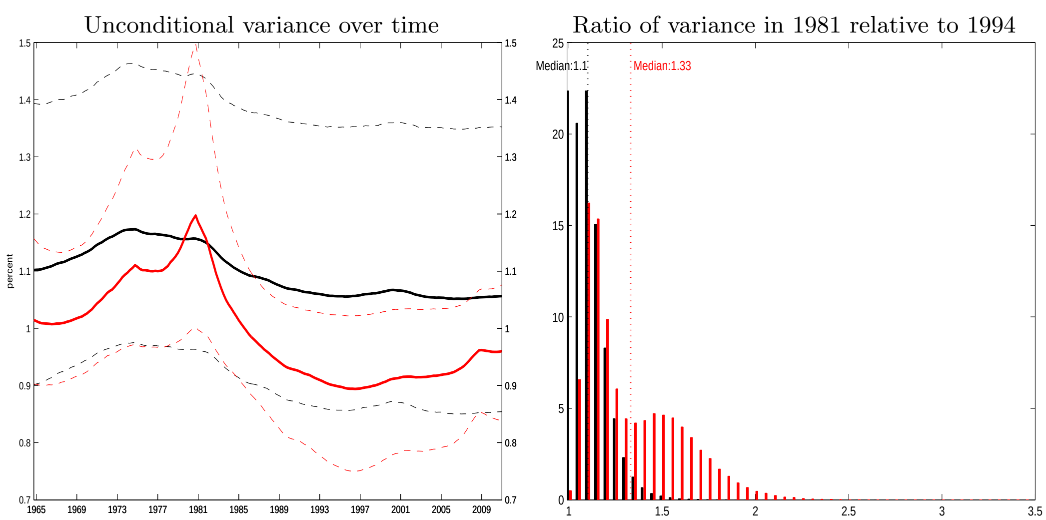
Notes: Numbers shown for the posterior mean and the 90% intervals of the SV persistence parameter.

Figure A.9: Results using SV-S specification.

Output Growth: Counterfactual evolution with Student's t component turned off



Output Growth: SV versus SV + Student's t



Notes: Top panels: Black lines are the historical evolution of the variable, and magenta lines are the median counterfactual evolution of the same variable if we shut down the Student-t distributed component of all shocks. The rolling window standard deviation uses 20 quarters before and 20 quarters after a given quarter. Southwest panel: Black line is the unconditional standard deviation in the estimation with both stochastic volatility and Student-t components, while the red line is the unconditional variance in the estimation with stochastic volatility component only. Southeast panel: Black bars correspond to the posterior histogram of the ratio of volatility in 1981 over the variance in 1994 for the estimation with both stochastic volatility and Student-t components, while the red bars are for the estimation with with stochastic volatility component only.

A.11 Subsample Analysis

Table A.23: Log-Marginal Likelihoods, Sub-samples

	Sample Ending in 2004Q4		*Sample Starting in 1984Q1*		*Sample Starting in 1991Q4*	
	Constant Volatility	Stochastic Volatility	Constant Volatility	Stochastic Volatility	Constant Volatility	Stochastic Volatility
Gaussian shocks						
	-964.0	-936.5	-521.3	-526.5	-378.1	-382.1
Student's t distributed shocks						
$\underline{\lambda} = 15$	-881.6	-870.1	-476.8	-479.56	-348.5	-341.9
$\underline{\lambda} = 9$	-870.6	-849.0	-471.1	-469.9	-339.5	-333.1
$\underline{\lambda} = 6$	-858.8	-844.1	-460.4	-462.2	-329.9	-328.1

Notes: The parameter $\underline{\lambda}$ represents the prior mean for the degrees of freedom in the Student's t distribution.

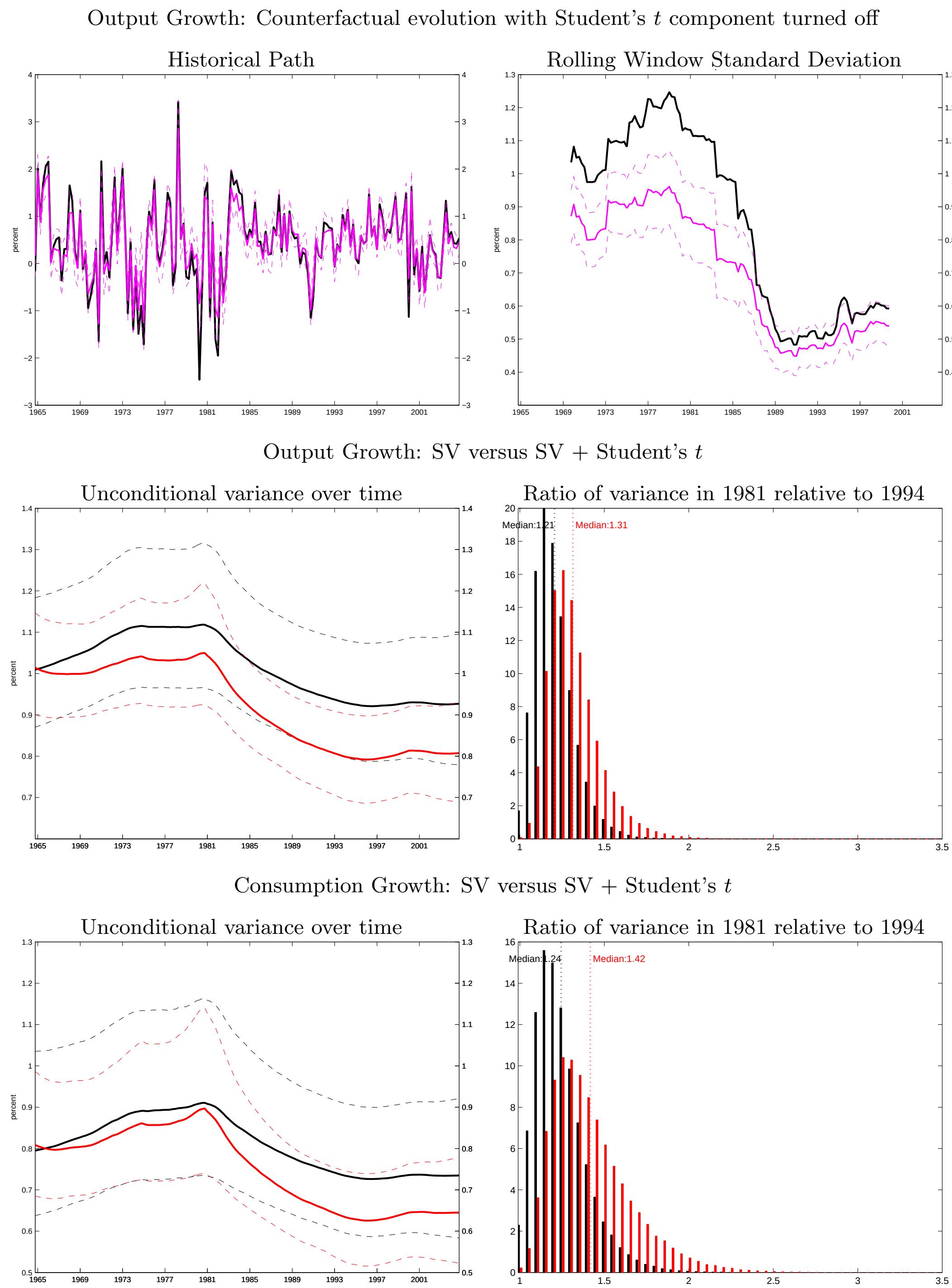
A.11.1 Sample Ending in 2004Q4

Table A.24: Posterior of the Student's t Degrees of Freedom, Sample Ending in 2004Q4

	Without Stochastic Volatility			*With Stochastic Volatility*		
	$\underline{\lambda} = 15$	$\underline{\lambda} = 9$	$\underline{\lambda} = 6$	$\underline{\lambda} = 15$	$\underline{\lambda} = 9$	$\underline{\lambda} = 6$
Government (g)	10.8	7.7	6.1	11.2	8.0	6.3
	(3.5,18.4)	(3.1,12.4)	(2.8,9.4)	(3.7,18.8)	(3.3,12.7)	(2.9,9.6)
Discount (b)	8.6	6.8	5.7	9.4	7.2	5.7
	(3.4,14.0)	(3.2,10.5)	(2.8,8.4)	(3.3,15.5)	(3.1,11.2)	(2.8,8.6)
MEI (μ)	11.0	8.0	6.5	11.3	8.3	6.6
	(3.7,18.4)	(3.3,12.7)	(3.1,9.8)	(3.8,19.0)	(3.4,13.1)	(3.1,10.1)
TFP (z)	5.3	4.5	3.9	6.5	5.0	4.3
	(2.0,8.7)	(2.0,6.9)	(2.0,5.8)	(2.3,11.0)	(2.2,7.9)	(2.1,6.5)
Price Markup (λ_f)	10.5	7.5	6.1	11.7	8.5	7.0
	(3.4,17.9)	(3.1,12.0)	(2.9,9.3)	(4.0,19.5)	(3.5,13.4)	(3.2,10.7)
Wage Markup (λ_w)	10.9	8.1	6.5	12.1	8.8	6.9
	(3.8,18.1)	(3.5,12.6)	(3.2,9.7)	(4.2,20.1)	(3.7,13.7)	(3.4,10.3)
Policy (r^m)	3.2	3.0	2.9	9.4	7.0	5.6
	(1.7,4.6)	(1.7,4.3)	(1.7,4.1)	(2.6,16.6)	(2.5,11.4)	(2.4,8.8)

Notes: Numbers shown for the posterior mean and the 90% intervals of the degrees of freedom parameter.

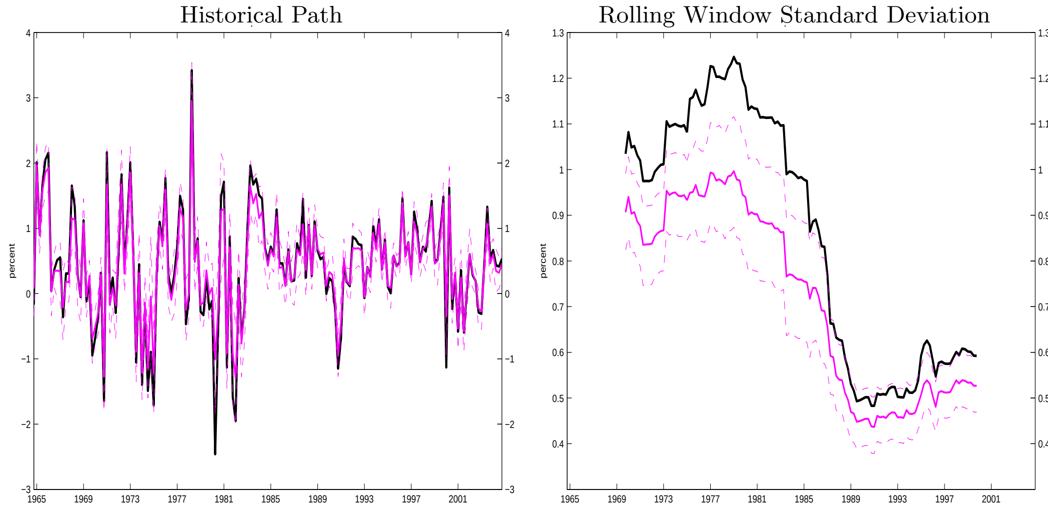
Figure A.10: Results for sub-sample ending in 2004Q4.



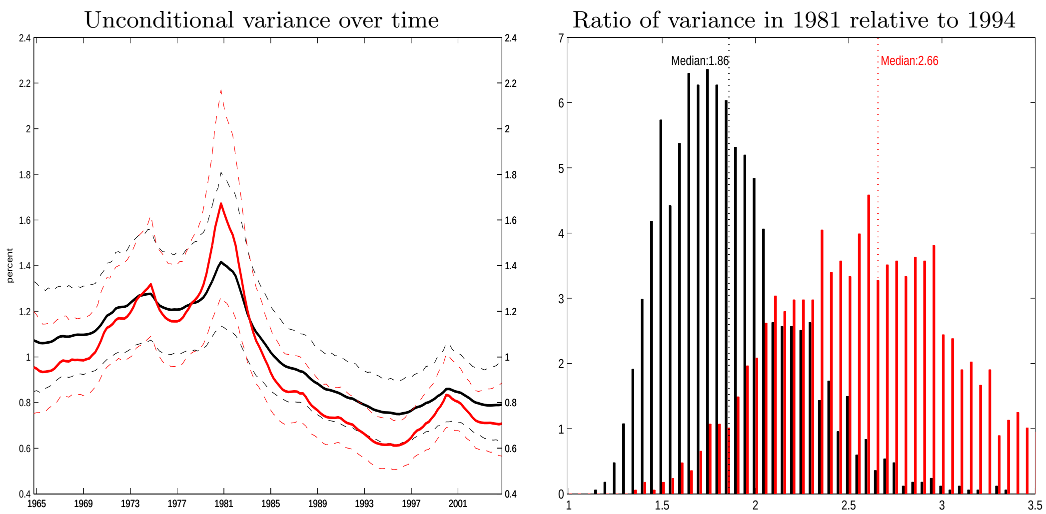
Notes: Top panels: Black lines are the historical evolution of the variable, and magenta lines are the median counterfactual evolution of the same variable if we shut down the Student-t distributed component of all shocks. The rolling window standard deviation uses 20 quarters before and 20 quarters after a given quarter. Southwest panel: Black line is the unconditional standard deviation in the estimation with both stochastic volatility and Student-t components, while the red line is the unconditional variance in the estimation with stochastic volatility component only. Southeast panel: Black bars correspond to the posterior histogram of the ratio of volatility in 1981 over the variance in 1994 for the estimation with both stochastic volatility and Student-t components, while the red bars are for the estimation with with stochastic volatility component only.

Figure A.11: Results using JPR Algorithm — sub-sample ending in 2004Q4

Output Growth: Counterfactual evolution with Student's t component turned off

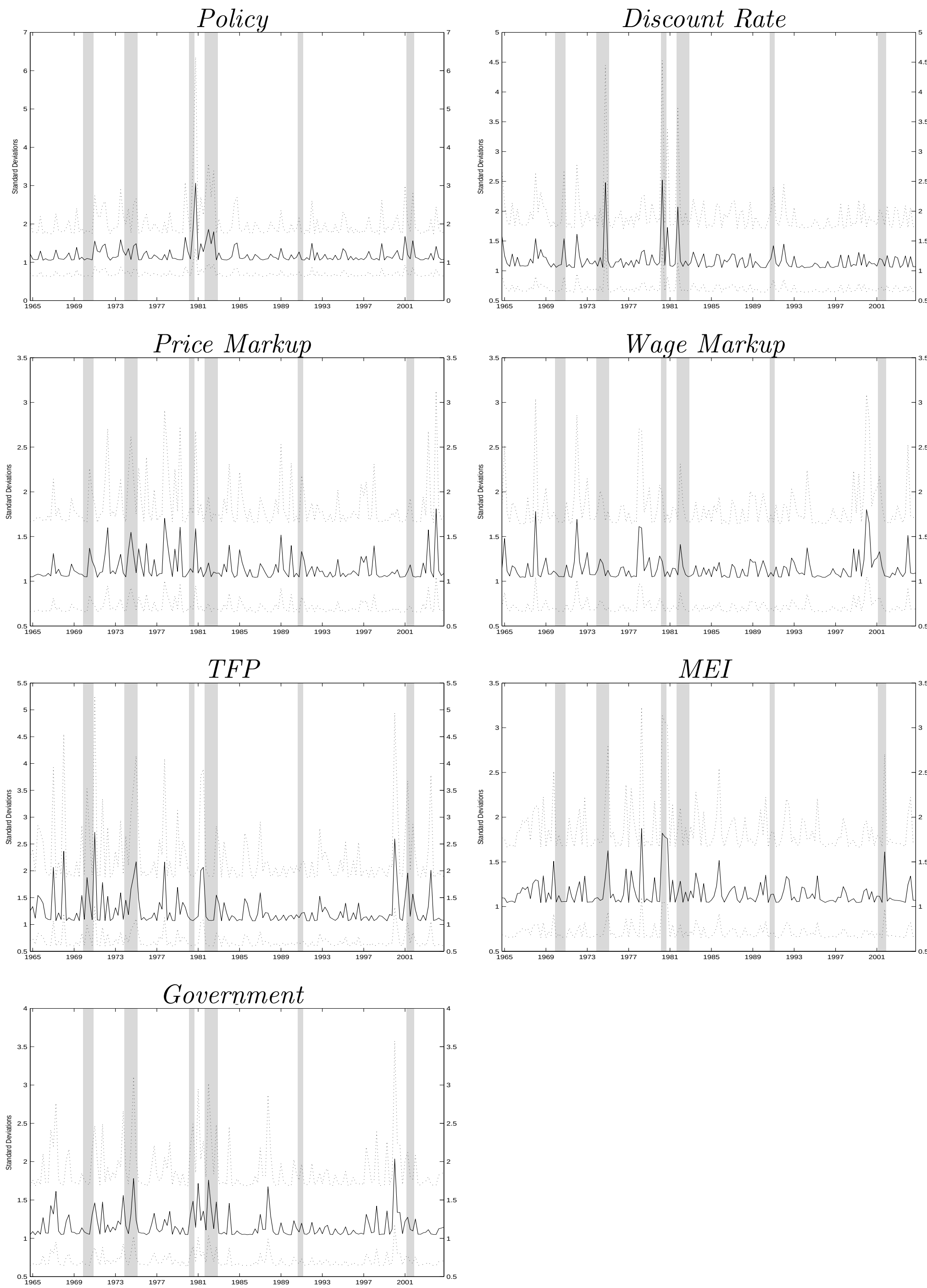


Output Growth: SV versus SV + Student's t



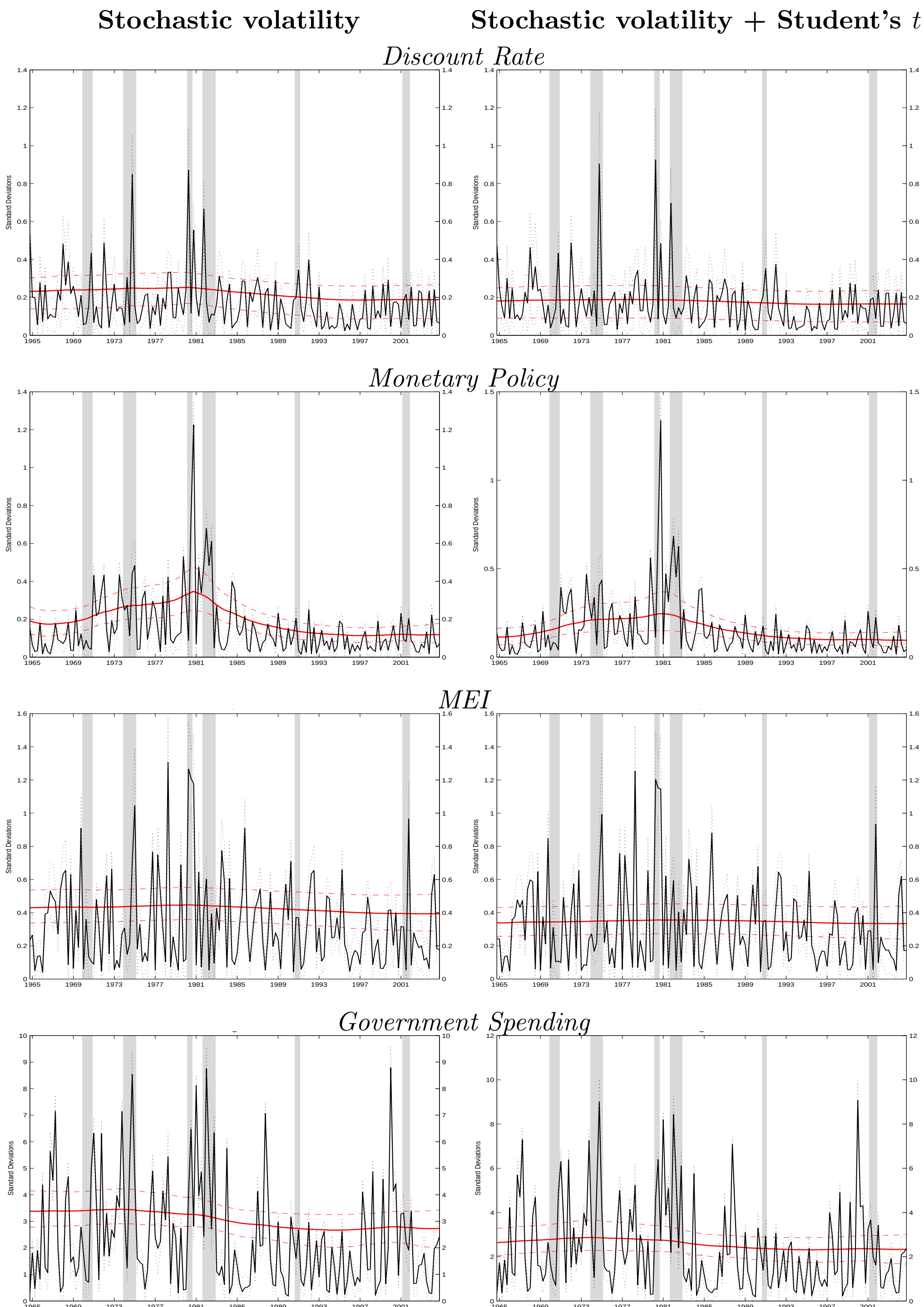
Notes: Top panels: Black lines are the historical evolution of the variable, and magenta lines are the median counterfactual evolution of the same variable if we shut down the Student-t distributed component of all shocks. The rolling window standard deviation uses 20 quarters before and 20 quarters after a given quarter. Southwest panel: Black line is the unconditional standard deviation in the estimation with both stochastic volatility and Student-t components, while the red line is the unconditional variance in the estimation with stochastic volatility component only. Southeast panel: Black bars correspond to the posterior histogram of the ratio of volatility in 1981 over the variance in 1994 for the estimation with both stochastic volatility and Student-t components, while the red bars are for the estimation with with stochastic volatility component only.

Figure A.12: $\tilde{h}_{q,t}^{-1/2}$ — sub-sample ending in 2004Q4



Notes: Estimation with Student's t distribution with $\underline{\lambda} = 6$. The solid line is the median, and the dashed lines are the posterior 90% bands. Black line is the absolute value of the shock, and the red line is the stochastic volatility component.

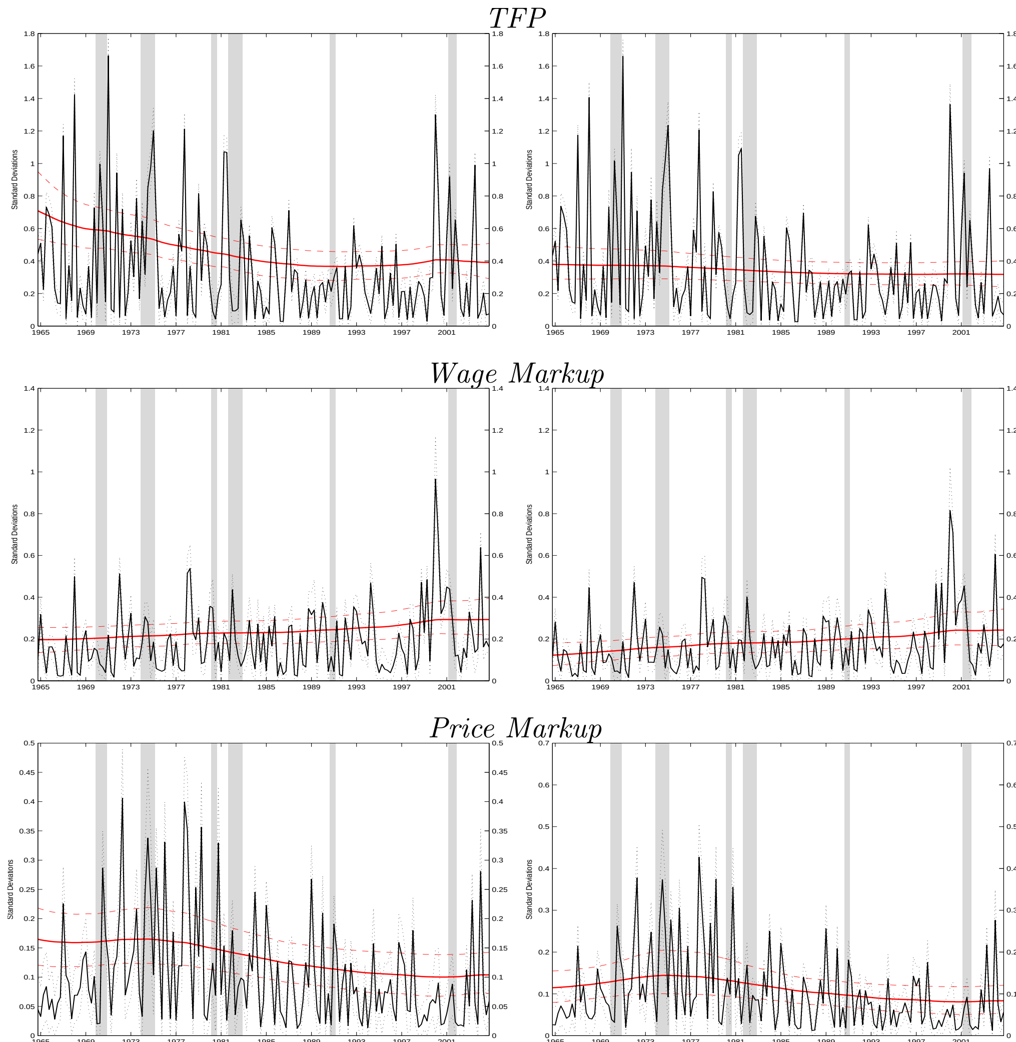
Figure A.13: Shocks (absolute values) and smoothed stochastic volatility component, $\sigma_{q,t}$ — subsample ending in 2004Q4



Notes: Estimation with Student's t distribution with $\underline{\lambda} = 6$. The solid line is the median, and the dashed lines are the posterior 90% bands. Black line is the absolute value of the shock, and the red line is the stochastic volatility component.

Figure A.13 — Continued

Stochastic volatility **Stochastic volatility + Student's t**



Notes: Estimation with Student's t distribution with $\underline{\lambda} = 6$. The solid line is the median, and the dashed lines are the posterior 90% bands. Black line is the absolute value of the shock, and the red line is the stochastic volatility component.

Table A.25: Comparison of Parameter Estimates: Subsample ending in 2004Q4 vs. full sample

	Full Sample				To 2004Q4			
	Base	SV	TD	SVTD	Base	SV	TD	SVTD
α	0.15	0.134	0.15	0.135	0.174	0.17	0.181	0.179
ζ_p	0.734	0.78	0.808	0.846	0.696	0.776	0.763	0.82
ι_p	0.315	0.344	0.383	0.286	0.291	0.306	0.313	0.289
Φ	1.58	1.518	1.575	1.551	1.704	1.686	1.719	1.677
S''	4.686	5.013	5.07	5.651	6.114	6.693	7.169	6.516
h	0.611	0.609	0.582	0.571	0.703	0.703	0.734	0.68
ψ	0.714	0.734	0.67	0.666	0.626	0.637	0.547	0.521
ν_l	2.088	2.212	2.3	2.476	2.349	2.67	2.601	2.636
ζ_w	0.803	0.826	0.83	0.843	0.756	0.802	0.812	0.829
ι_w	0.541	0.547	0.495	0.511	0.584	0.554	0.528	0.501
β	0.206	0.184	0.202	0.175	0.167	0.151	0.162	0.161
ψ_1	1.953	1.866	1.82	1.884	2.066	2.071	1.957	1.934
ψ_2	0.083	0.073	0.115	0.116	0.09	0.104	0.12	0.138
ψ_3	0.245	0.217	0.213	0.184	0.238	0.207	0.193	0.189
π^*	0.683	0.719	0.706	0.808	0.709	0.784	0.756	0.847
σ_c	1.236	1.109	1.248	1.274	1.406	1.426	1.471	1.42
ρ	0.835	0.854	0.875	0.875	0.825	0.852	0.867	0.874
γ	0.306	0.321	0.356	0.389	0.415	0.421	0.431	0.434
$\bar{L}$	-44.17	-46.67	-43.38	-44.73	-42.897	-43.542	-43.348	-44.265
ρ_g	0.977	0.977	0.982	0.988	0.98	0.981	0.98	0.981
ρ_b	0.758	0.845	0.844	0.852	0.285	0.335	0.279	0.453
ρ_μ	0.748	0.753	0.791	0.806	0.735	0.739	0.746	0.772
ρ_z	0.994	0.991	0.987	0.981	0.963	0.961	0.959	0.963
ρ_{λ_f}	0.791	0.797	0.811	0.83	0.891	0.831	0.893	0.863
ρ_{λ_w}	0.981	0.952	0.962	0.923	0.969	0.951	0.928	0.902
ρ_{rm}	0.154	0.219	0.219	0.227	0.145	0.15	0.183	0.179
σ_g	2.892	3.169	2.387	2.665	3.091	3.388	2.566	2.654
σ_b	0.125	0.122	0.072	0.1	0.232	0.23	0.192	0.163
σ_μ	0.43	0.454	0.325	0.3	0.435	0.43	0.35	0.334
σ_z	0.493	0.869	0.362	0.473	0.463	0.717	0.331	0.38
σ_{λ_f}	0.164	0.191	0.163	0.127	0.136	0.166	0.111	0.117
σ_{λ_w}	0.281	0.203	0.213	0.151	0.255	0.197	0.188	0.12
σ_{rm}	0.228	0.243	0.133	0.095	0.235	0.196	0.133	0.112
η_{gz}	0.787	0.775	0.786	0.765	0.747	0.736	0.74	0.736
η_{λ_f}	0.67	0.749	0.815	0.734	0.73	0.681	0.771	0.775
η_{λ_w}	0.948	0.914	0.924	0.865	0.887	0.876	0.833	0.797

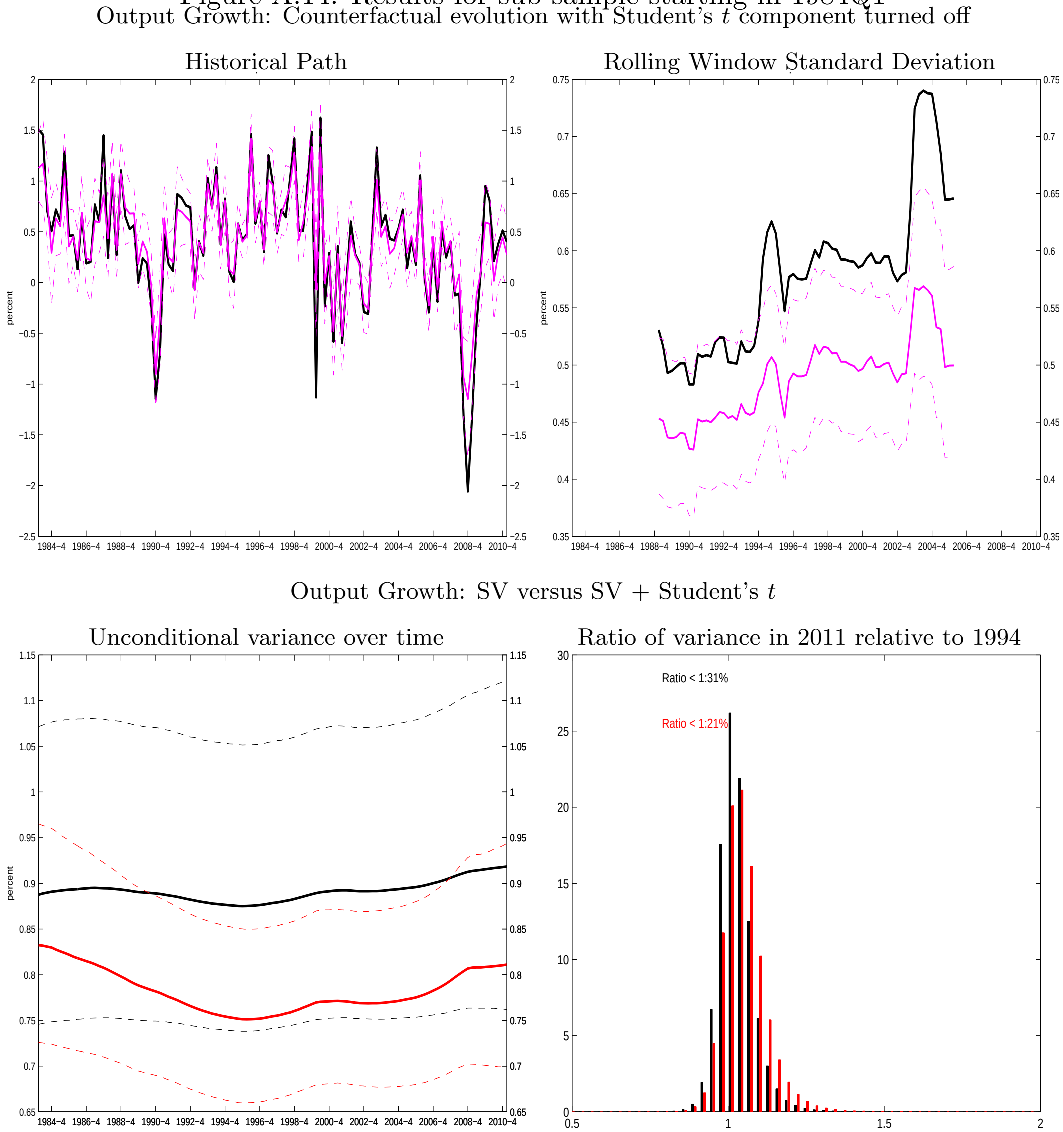
A.11.2 Sample Starting in 1984Q1

Table A.26: Posterior of the Student's t Degrees of Freedom, Sample Starting in 1984Q1

	Without Stochastic Volatility			*With Stochastic Volatility*		
	$\underline{\lambda} = 15$	$\underline{\lambda} = 9$	$\underline{\lambda} = 6$	$\underline{\lambda} = 15$	$\underline{\lambda} = 9$	$\underline{\lambda} = 6$
Government (g)	7.6	5.8	4.8	7.6	5.7	4.7
	(2.4, 13.2)	(2.3, 9.3)	(2.2, 7.4)	(2.4, 13.2)	(2.3, 9.1)	(2.1, 7.3)
Discount (b)	9.6	6.9	5.6	9.6	7.0	5.6
	(2.9, 16.4)	(2.7, 11.2)	(2.5, 8.6)	(2.9, 16.4)	(2.7, 11.3)	(2.5, 8.7)
MEI (μ)	10.0	7.6	6.1	10.0	7.5	6.0
	(3.3, 17.0)	(3.1, 12.0)	(2.8, 9.3)	(3.4, 17.0)	(3.0, 11.8)	(2.8, 9.2)
TFP (z)	6.8	5.2	4.3	7.5	5.6	4.6
	(2.1, 11.8)	(2.1, 8.4)	(2.0, 6.7)	(2.3, 13.1)	(2.2, 9.1)	(2.1, 7.2)
Price Markup (λ_f)	8.9	6.4	5.1	10.3	7.0	5.5
	(2.5, 15.7)	(2.2, 10.4)	(2.2, 8.0)	(2.8, 18.0)	(2.6, 11.6)	(2.3, 8.6)
Wage Markup (λ_w)	9.5	7.2	5.8	10.4	7.6	6.1
	(3.1, 16.2)	(2.9, 11.4)	(2.7, 8.8)	(3.3, 17.7)	(3.1, 12.2)	(2.8, 9.4)
Policy (r^m)	10.6	7.6	6.1	10.9	7.7	6.0
	(3.3, 18.0)	(3.0, 12.3)	(2.7, 9.3)	(3.3, 18.5)	(3.0, 12.4)	(2.7, 9.3)

Notes: Numbers shown for the posterior mean and the 90% intervals of the degrees of freedom parameter.

Figure A.14: Results for sub-sample starting in 1984Q1



Notes: Top panels: Black lines are the historical evolution of the variable, and magenta lines are the median counterfactual evolution of the same variable if we shut down the Student-t distributed component of all shocks. The rolling window standard deviation uses 20 quarters before and 20 quarters after a given quarter. Southwest panel: Black line is the unconditional standard deviation in the estimation with both stochastic volatility and Student-t components, while the red line is the unconditional variance in the estimation with stochastic volatility component only. Southeast panel: Black bars correspond to the posterior histogram of the ratio of volatility in 2011 over the variance in 1994 for the estimation with both stochastic volatility and Student-t components, while the red bars are for the estimation with with stochastic volatility component only.

A.11.3 Sample Starting in 1991Q4

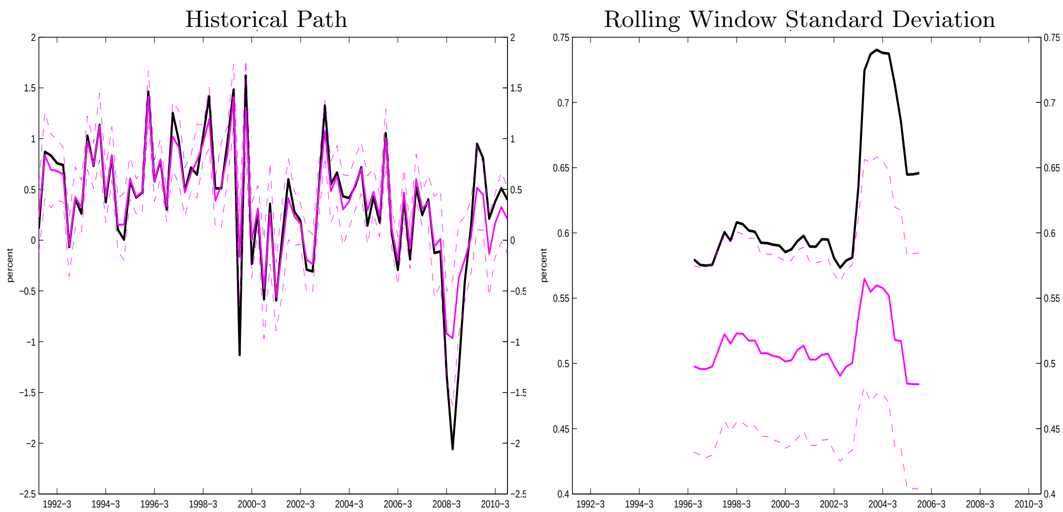
Table A.27: Posterior of the Student's t Degrees of Freedom, Sample Starting in 1991Q4

	Without Stochastic Volatility			*With Stochastic Volatility*		
	$\underline{\lambda} = 15$	$\underline{\lambda} = 9$	$\underline{\lambda} = 6$	$\underline{\lambda} = 15$	$\underline{\lambda} = 9$	$\underline{\lambda} = 6$
Government (g)	9.9	6.9	5.4	10.0	7.1	5.5
	(2.7,17.1)	(2.5,11.4)	(2.2,8.5)	(2.7,17.5)	(2.5,11.6)	(2.3,8.7)
Discount (b)	9.8	7.4	5.6	10.1	7.3	5.8
	(3.0,16.9)	(2.8,12.0)	(2.4,8.7)	(3.0,17.4)	(2.7,11.8)	(2.5,9.1)
MEI (μ)	7.0	5.5	4.6	7.2	5.6	4.6
	(2.3,11.9)	(2.1,8.8)	(2.0,7.2)	(2.3,12.3)	(2.2,9.1)	(2.0,7.2)
TFP (z)	7.6	5.4	4.2	7.9	5.6	4.4
	(1.9,13.9)	(1.8,9.1)	(1.7,6.8)	(2.0,14.3)	(1.9,9.4)	(1.8,7.1)
Price Markup (λ_f)	6.2	5.0	3.7	10.0	6.9	5.4
	(1.6,11.2)	(1.7,8.4)	(1.5,6.0)	(2.1,18.2)	(1.9,11.7)	(1.9,8.9)
Wage Markup (λ_w)	10.6	7.4	5.7	10.7	7.4	5.8
	(3.0,18.3)	(2.6,12.1)	(2.4,9.0)	(3.0,18.5)	(2.6,12.2)	(2.4,9.1)
Policy (r^m)	11.7	7.8	5.9	11.7	7.9	5.9
	(3.1,20.2)	(2.6,12.9)	(2.4,9.4)	(3.1,20.1)	(2.7,13.0)	(2.4,9.4)

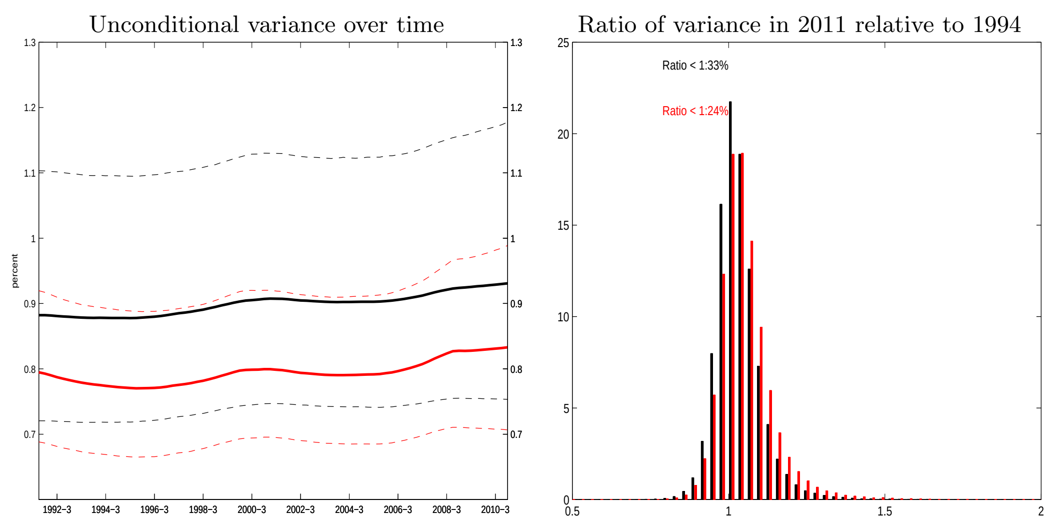
Notes: Numbers shown for the posterior mean and the 90% intervals of the degrees of freedom parameter.

Figure A.15: Results for sub-sample starting in 1991Q4

Output Growth: Counterfactual evolution with Student's t component turned off



Output Growth: SV versus SV + Student's t



Notes: Top panels: Black lines are the historical evolution of the variable, and magenta lines are the median counterfactual evolution of the same variable if we shut down the Student-t distributed component of all shocks. The rolling window standard deviation uses 20 quarters before and 20 quarters after a given quarter. Southwest panel: Black line is the unconditional standard deviation in the estimation with both stochastic volatility and Student-t components, while the red line is the unconditional variance in the estimation with stochastic volatility component only. Southeast panel: Black bars correspond to the posterior histogram of the ratio of volatility in 2011 over the variance in 1994 for the estimation with both stochastic volatility and Student-t components, while the red bars are for the estimation with with stochastic volatility component only.