

Online Appendix

This is an online appendix to Kadan, Ohad and Asaf Manela, Estimating the Value of Information.

A Estimation details

Carr and Wu (2010) show that, under the assumptions of their LNV model, implied variance as a function of log moneyness k and time to maturity τ is determined by a quadratic equation:

$$\begin{aligned} & \frac{w_t^2}{4} e^{-2\eta_t \tau} \tau^2 I_t^4(k, \tau) + \left[1 + \kappa_t \tau + w_t^2 e^{-2\eta_t \tau} \tau - \rho_t s_t w_t e^{-\eta_t \tau} \tau \right] I_t^2(k, \tau) \\ & - \left[s_t^2 + \kappa_t \theta_t \tau + 2\rho_t s_t w_t e^{-\eta_t \tau} k + w_t^2 e^{-2\eta_t \tau} k^2 \right] = 0. \end{aligned} \quad (1)$$

The whole implied variance surface is then determined by the six coefficients $(\kappa_t, w_t, \eta_t, \theta_t, s_t, \rho_t)$, which are related to the stock price and implied variance dynamics. It turns out that these parameters are underidentified, so we fix $\kappa_t = 1$. To keep the variables to their respective domains, we follow Carr and Wu and optimize over the transformed variables $(\tilde{w}_t, \tilde{\eta}_t, \tilde{\theta}_t, \tilde{s}_t, \tilde{\rho}_t)$, which are defined on the entire real line. The first four are logs of the original parameters, and $\rho_t = \frac{e^{\tilde{\rho}_t} - 1}{e^{\tilde{\rho}_t} + 1} \in [-1, 1]$.

Let $h(k, \tau; \tilde{w}_t, \tilde{\eta}_t, \tilde{\theta}_t, \tilde{s}_t, \tilde{\rho}_t)$ denote the LNV model implied volatility, i.e. the square root of the sole real positive root of (1). Given a sample of options i on date t , with moneyness k_{it} , terms τ_{it} , and Black-Scholes implied volatility y_{it} , we estimate the five parameters using weighted nonlinear least squares,

$$y_{it} = h(k_{it}, \tau_{it}; \tilde{w}_t, \tilde{\eta}_t, \tilde{\theta}_t, \tilde{s}_t, \tilde{\rho}_t) + \varepsilon_{it}, \quad (2)$$

with weights $e^{-\kappa_i^2/2}$, so that at the money options get the most weight.

Assuming the implied volatility function only depends on the relative return (moneyness) and term, but not the index level S , day t implied volatility given any spot price S , strike K , and term τ is

$$\sigma_t(S, K, \tau) = h(\log(K/S), \tau; \tilde{w}_t, \tilde{\eta}_t, \tilde{\theta}_t, \tilde{s}_t, \tilde{\rho}_t). \quad (3)$$

European put option premia on date t are

$$Put_t(S, K, \tau) = BS Put(S, K, \sigma_t(S, K, \tau), r_{ft}^{(\tau)}, \tau, \delta_t), \quad (4)$$

where $r_{ft}^{(\tau)}$ is the annualized continuously compounded risk free rate over horizon τ and δ_t is the dividend yield. Note that nowhere do we assume the Black-Scholes pricing formula is correct. It serves here only as a mathematically convenient transformation.

In estimating state prices, we follow the risk-neutral CDF-based approach of [Liu \(2014\)](#) so as not to miss probability mass at the tails. Let $A_t(S, K, \tau)$ denote the derivative of the put option price with respect to its strike. It can easily be verified that A_t equals the risk-neutral CDF of the spot price at maturity S_τ discounted at the riskfree rate ([Breedon and Litzenberger 1978](#)):

$$A_t(S, K, \tau) \equiv \frac{\partial Put_t(S, K, \tau)}{\partial K} = e^{-r_{ft}^{(\tau)} \times \tau} P_{r^{\text{risk-neutral}}}(S_\tau \leq K). \quad (5)$$

On each day t , we discretize the state space relative to the current spot price S_t . With a constant log return difference dk between states, the possible states are $S_{jt+\tau} = S_t e^{r_j^{mkt}} = S_t e^{(j-c) \times dk}$, where c is the middle row's index (if $n = 11$, $c = 6$). Because we are discretizing a continuous state variable, which may lie beyond the n points, we regard the state as being

$$S = K_i \text{ if } \begin{cases} S \in [0, K_i e^{dk/2}] & i = 1 \\ S \in [K_i e^{-dk/2}, K_i e^{dk/2}] & i = 2, \dots, n-1 \\ S \in [K_i e^{-dk/2}, \infty] & i = n, \end{cases} \quad (6)$$

so that the price of security paying 1 in state K_i and 0 otherwise is

$$q_t(S, K_i, \tau) = \begin{cases} A_t(S, K_i e^{dk/2}, \tau) & i = 1 \\ A_t(S, K_i e^{dk/2}, \tau) - A_t(S, K_i e^{-dk/2}, \tau) & i = 2, \dots, n-1 \\ A_t(S, \infty, \tau) - A_t(S, K_i e^{-dk/2}, \tau) & i = n. \end{cases} \quad (7)$$

Finally, each entry in row i and column j of the time t state price transition matrix over horizon τ is given by $q_{tij} = q_t(S_i, S_j, \tau)$, for $i, j = 1 \dots n$.

Numerically, some states have zero state price in one period but a positive price after the signal is received. These are theoretically arbitrage opportunities, which we eliminate by setting the prior probability to equal the posterior and then rescale to keep the same risk-free discount factor (sum of q_{tij} over j).

B Robustness

We check whether our results change as we revisit some of the choices we made in the estimation.

B.1 Relaxing and testing for rational expectations

Our estimates thus far impose that recovered probabilities are rational in the sense that they satisfy (34). Table 1 reports the value of information for the same sets of parameters reported previously in Table 2, but this time without imposing rational expectations ($\pi_{ij} = 0$ for all i, j) and omitting the additional moments (47). The point estimates are quite similar. Standard errors are somewhat larger, but still allow us to distinguish between some information sources. This larger parameter uncertainty reflects the standard tension between efficiency and robustness (see Cochrane 2005, Ch. 16).

Our GMM framework provides a test for rational expectations. Table 1 reports p-values of a χ^2 statistic testing the null hypothesis that the recovered probabilities satisfy the additional rational expectations restrictions (47). These show that we can statistically reject rational expectations only in the case of jobless claims reports at commonly-used significance levels.

B.2 Formal difference tests

Table 2 presented estimates and standard errors per signal but did not formally test whether these are different across signals. For completeness Table 2 reports p -values of a t statistic testing the null hypothesis that the event in each row is more valuable than the event in the column. It shows, for example, that employment reports are statistically more valuable than most events at common

Table 1: **Relaxing and Testing for Rational Expectations: Value of Private Information**

Panel A: One-time Signal

Event	$RRA = 10, EIS = 1.5$			$RRA = 10 = 1/EIS$			$RRA = 1 = 1/EIS$			Obs
	Ω	$se(\Omega)$	$p(\chi^2)$	Ω	$se(\Omega)$	$p(\chi^2)$	Ω	$se(\Omega)$	$p(\chi^2)$	
Consumer Conf.	0.039	(0.003)	0.351	0.035	(0.004)	0.998	0.405	(0.042)	0.350	574
Employment	0.053	(0.005)	1.000	0.059	(0.007)	1.000	0.540	(0.053)	1.000	207
FOMC	0.039	(0.006)	1.000	0.042	(0.009)	1.000	0.355	(0.053)	1.000	133
Pre-FOMC	0.042	(0.009)	1.000	0.034	(0.006)	1.000	0.466	(0.107)	1.000	134
GDP	0.034	(0.003)	1.000	0.033	(0.004)	1.000	0.349	(0.034)	1.000	206
Jobless Claims	0.043	(0.003)	0.001	0.042	(0.003)	0.318	0.441	(0.031)	0.001	887
Mortgage App.	0.037	(0.003)	0.449	0.035	(0.004)	0.994	0.368	(0.032)	0.443	570

Panel B: Signal Every Period

Event	$RRA = 10, EIS = 1.5$			$RRA = 10 = 1/EIS$			$RRA = 1 = 1/EIS$			Obs
	Ω	$se(\Omega)$	$p(\chi^2)$	Ω	$se(\Omega)$	$p(\chi^2)$	Ω	$se(\Omega)$	$p(\chi^2)$	
Consumer Conf.	13.95	(1.24)	0.35	8.27	(0.77)	0.99	77.56	(3.30)	0.35	574
Employment	22.93	(2.61)	1.00	12.13	(1.08)	1.00	85.82	(2.49)	1.00	207
FOMC	16.21	(2.65)	1.00	8.68	(1.70)	1.00	74.36	(4.99)	1.00	133
Pre-FOMC	17.14	(3.35)	1.00	7.42	(1.39)	1.00	79.41	(6.99)	1.00	134
GDP	14.29	(1.69)	1.00	7.10	(0.69)	1.00	70.88	(3.49)	1.00	206
Jobless Claims	17.89	(1.20)	0.00	8.92	(0.53)	0.32	78.90	(2.18)	0.00	887
Mortgage App.	13.09	(0.97)	0.45	8.27	(0.77)	0.99	74.36	(2.70)	0.44	570

Reported are GMM estimates for the state-dependent value of information as percent of wealth Ω for the middle (current) state of the 11 states. The first set of results uses the benchmark parameters: $\beta = 0.998$, $\gamma = 10$, $\rho = 1/1.5$, and $\tau = 1/12$ (Bansal and Yaron, 2004). The second set is expected utility with $\gamma = \rho = 10$. The third set is the log utility limiting case. Newey-West standard errors in parentheses correct for autocorrelation in errors with two lags. $p(\chi^2)$ is the p-value of a χ^2 statistic testing the null hypothesis that the recovered probabilities satisfy the additional rational expectations restrictions (47).

significant levels, and that jobless claims dominate GDP and mortgage application reports in this statistical sense.

Table 2: **Difference Tests Across Signals**

Panel A: One-time Signal

Event	Consumer Conf.	Employment	FOMC	Pre-FOMC	GDP	Jobless Claims	Mortgage App.
Consumer Conf.	0.500	0.994	0.238	0.405	0.138	0.794	0.151
Employment	0.006	0.500	0.003	0.010	0.000	0.020	0.000
FOMC	0.762	0.997	0.500	0.653	0.432	0.924	0.481
Pre-FOMC	0.595	0.990	0.347	0.500	0.268	0.813	0.299
GDP	0.862	1.000	0.568	0.732	0.500	0.981	0.570
Jobless Claims	0.206	0.980	0.076	0.187	0.019	0.500	0.015
Mortgage App.	0.849	1.000	0.519	0.701	0.430	0.985	0.500

Panel B: Signal Every Period

Event	Consumer Conf.	Employment	FOMC	Pre-FOMC	GDP	Jobless Claims	Mortgage App.
Consumer Conf.	0.50	1.00	0.66	0.82	0.58	0.98	0.15
Employment	0.00	0.50	0.00	0.00	0.00	0.01	0.00
FOMC	0.34	1.00	0.50	0.88	0.42	0.99	0.01
Pre-FOMC	0.18	1.00	0.12	0.50	0.20	0.95	0.01
GDP	0.42	1.00	0.58	0.80	0.50	0.98	0.08
Jobless Claims	0.02	0.99	0.01	0.05	0.02	0.50	0.00
Mortgage App.	0.85	1.00	0.99	0.99	0.92	1.00	0.50

Reported are p -values of a t statistic testing the null hypothesis that the event in each row is more valuable than the event in the column. Results are based on the benchmark parameters: $\beta = 0.998$, $\gamma = 10$, $\rho = 1/1.5$, and $\tau = 1/12$ (Bansal and Yaron, 2004).

B.3 Modifying the empirical design

A potentially important calibration parameter is the exponential tilt ϵ of the stochastic discount factor (45), which we use to recover physical probabilities from options. As mentioned, we set $\epsilon = 1.5$ to match the equity premium in our sample. Figure 1a shows that modest increases in ϵ do not affect the value of one-time information, but increase the value of a signal every period. We do not plot higher values of ϵ because they result in risk premia so high that utility is often infinite.

Figure 1b shows that as we increase the number of states n used to discretize the state space, the estimated value of information is statistically indistinguishable from that of the benchmark, yet remains greater than zero throughout.

Another choice we had to make was the distance (in log returns) between states. A larger value captures better the tails of the distribution, especially in later periods, but also gives a more coarse estimate of the center of the distribution. Figure 1c shows that at least in the neighborhood of our benchmark estimates, this choice makes a negligible difference.

Finally, in our benchmark estimates, we stop the search for a minimum of the GMM objective at step i when $|\omega_{i+1} - \omega_i| \leq 10^{-8}$, that is when the change in the value of information is less than a basis point of a basis point. Figure 1d shows that increasing the numerical precision even to 10^{-10} does not substantially change our estimates.

C Delayed information

An important aspect of the value of information is the timing of its release. We can capture the effect of timing on the value of information by introducing into our framework a delay of $\Delta \equiv t^* - t \geq 0$ periods between the time t that the information is acquired and the time t^* when a one-time signal from information source α is received. Our baseline model corresponds to the case where $\Delta = 0$.

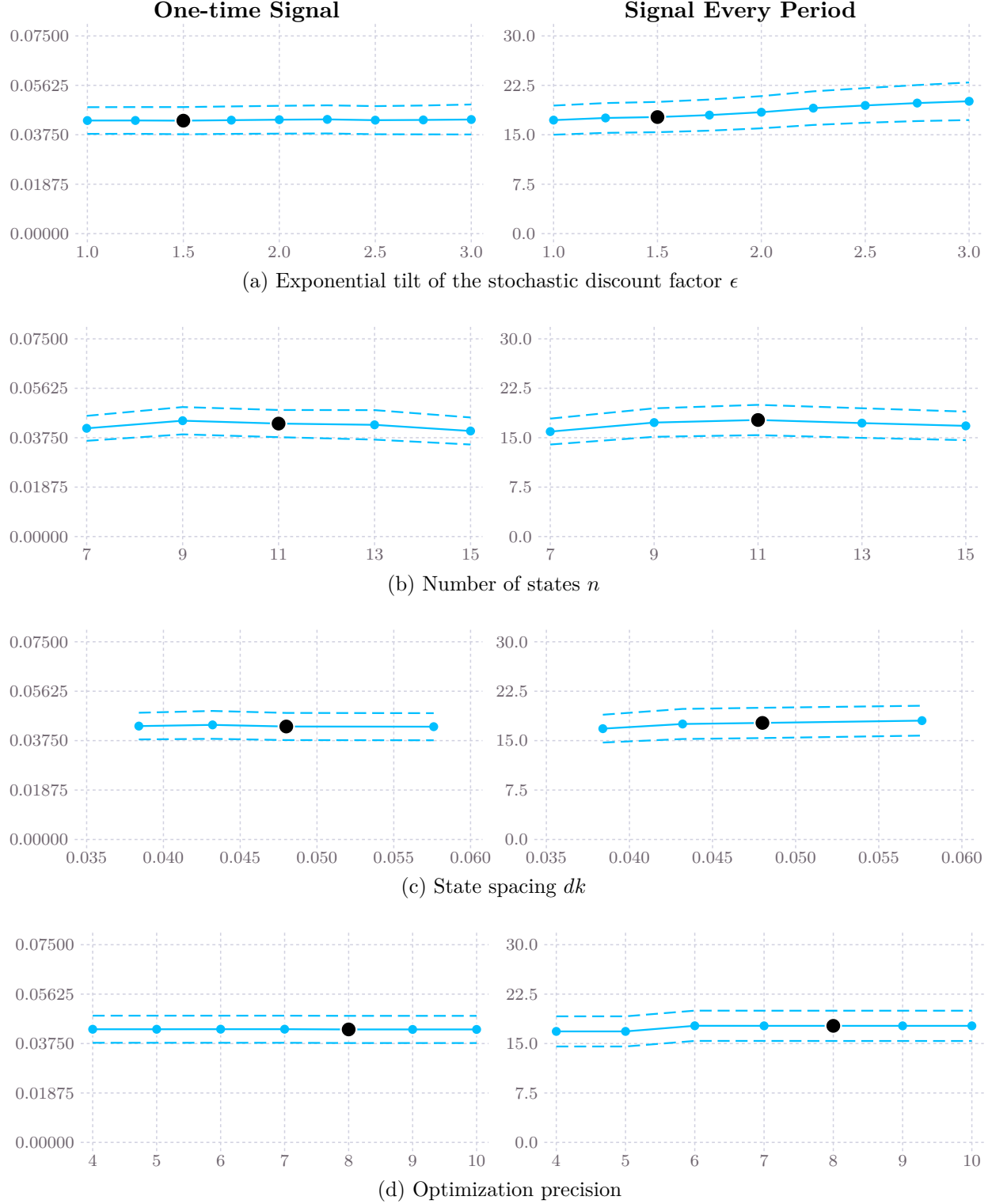


Figure 1: **Robustness: Value of Information on Jobless Claims**

We evaluate the robustness of our estimates by plotting the value of private information as percent of wealth around our benchmark estimate (circled). On each date we discretize the state relative to the current SPX closing price, so that log returns (or equivalently log moneyness) take one of n possible equally-spaced states r_j^{mkt} , centered around zero, where the space between each state is dk . Optimization precision is the defined as the power x such that we stop the search for a minimum of the GMM objective at step i when $|\omega_{i+1} - \omega_i| \leq 10^{-x}$. Physical probabilities are an exponentially-tilted version of state prices, $p_{ijm} \propto e^{\epsilon r_j^{mkt}} q_{ijm}$, governed by the parameter ϵ .

C.1 Model extension

The optimization problem in this case consists of several Bellman equations for various periods relative to t^* . For periods $t = 0, \dots, t^* - 2$ before the signal arrives,

$$V(a_t, z_t, \Delta; \alpha) = \max_{c_t, \mathbf{w}_{t+1}} \left\{ (1 - \beta) c_t^{1-\rho} + \beta E_t \left[V(a_{t+1}, z_{t+1}, \Delta - 1; \alpha)^{1-\gamma} \right]^{\frac{1-\rho}{1-\gamma}} \right\}^{\frac{1}{1-\rho}}. \quad (8)$$

At time $t = t^* - 1$, one period before the signal arrives,

$$V(a_{t^*-1}, z_{t^*-1}, 1; \alpha) = \max_{c_{t^*-1}, \mathbf{w}_{t^*}} \left\{ (1 - \beta) c_{t^*-1}^{1-\rho} + \beta E_{t^*-1} \left[V(a_{t^*}, z_{t^*}, s_{t^*}; \alpha)^{1-\gamma} \right]^{\frac{1-\rho}{1-\gamma}} \right\}^{\frac{1}{1-\rho}}. \quad (9)$$

At $t = t^*$, the value function depends on the signal,

$$V(a_{t^*}, z_{t^*}, s_{t^*}; \alpha) = \max_{c_{t^*}, \mathbf{w}_{t^*+1}} \left\{ (1 - \beta) c_{t^*}^{1-\rho} + \beta E_{t^*} \left[V(a_{t^*+1}, z_{t^*+1}; \alpha_0)^{1-\gamma} \right]^{\frac{1-\rho}{1-\gamma}} \right\}^{\frac{1}{1-\rho}}, \quad (10)$$

though all remaining periods $t > t^*$ do not and coincide with the uninformative benchmark α_0 ,

$$V(a_t, z_t; \alpha_0) = \max_{c_t, \mathbf{w}_{t+1}} \left\{ (1 - \beta) c_t^{1-\rho} + \beta E_t \left[V(a_{t+1}, z_{t+1}; \alpha_0)^{1-\gamma} \right]^{\frac{1-\rho}{1-\gamma}} \right\}^{\frac{1}{1-\rho}}. \quad (11)$$

All of the above are maximized subject to the same wealth constraint as before. Note that unlike in (7), the continuation value in (10) has no future signal because we focus on the one-time signal case.

We can now define formally the value of delayed information at $t = t^* - \Delta$.

Definition 1. The *value of information structure* α that yields a signal s_{t^*} at time $t^* = t + \Delta$, when the current state is state z_t is the fraction of wealth Ω such that

$$V(a_t(1 - \Omega), z_t, \Delta; \alpha) = V(a_t, z_t; \alpha_0). \quad (12)$$

Because $V(a_{t^*-1}, z_{t^*-1}; \alpha)$ does not condition on the signal, we do not need the outer certainty equivalent in its definition as we did in Definition 1.

Manipulation similar to that of Section 2 yields a recursive expression for the value of information delayed by $\Delta > 0$ periods,

$$\omega(z_t, \Delta; \alpha) = \frac{\rho}{1-\rho} \log \left\{ 1 - \beta + \beta^{\frac{1}{\rho}} [\Gamma(z_t, \Delta; \alpha)]^{\frac{\gamma}{\rho} \frac{1-\rho}{1-\gamma}} \right\} - \rho v(z_t; \alpha_0), \quad (13)$$

where

$$\Gamma(z_t, \Delta; \alpha) \equiv \sum_{z_{t+1}} p(z_{t+1}|z_t) e^{\frac{1-\gamma}{\gamma} [\rho v(z_{t+1}; \alpha_0) + \omega(z_{t+1}, \Delta-1; \alpha) + \log(p(z_{t+1}|z_t)/q(z_{t+1}|z_t))]}, \quad (14)$$

which can be calculated by iterating backwards from time t^* , when by definition $\omega(z_t, 0; \alpha) \equiv \omega(z_t; \alpha)$ —the value of nondelayed one-time information defined in Section 2.1.

C.2 Estimation and results

We estimate the mean value of a one-time signal from information source α , in state i , $\Delta \equiv t^* - t > 0$ periods before its arrival as

$$\hat{\omega}_i(\Delta; \alpha) = \frac{1}{T} \sum_{t=1}^T \left(\frac{\rho}{1-\rho} \log \left\{ 1 - \beta + \beta^{\frac{1}{\rho}} [\Gamma_{it}(\Delta; \alpha)]^{\frac{\gamma}{\rho} \frac{1-\rho}{1-\gamma}} \right\} - \rho v_{it}(\alpha_0) \right), \quad (15)$$

where

$$\Gamma_{it}(\Delta; \alpha) \equiv \sum_k p_{ikt} e^{\frac{1-\gamma}{\gamma} [\rho v_{kt}(\alpha_0) + \omega_k(\Delta-1; \alpha) + \log(p_{ikt}/q_{ikt})]}. \quad (16)$$

Figure 2 reports estimation results for our benchmark recursive utility parameters, and for the expected power utility and log utility special cases.

Our analysis captures two channels by which timing matters. The first channel, is that because the value of information in our model depends on the state z_t , so does the effect of delaying the signal. As a result, in good times, when the value of information is relatively low, delaying its arrival is beneficial because the value of information when it arrives is expected to be higher. The agent's risk aversion magnifies this effect because such high value of information states are also high marginal utility states. Conversely, in bad times, the value of information is higher than average and delaying can only decrease its value.

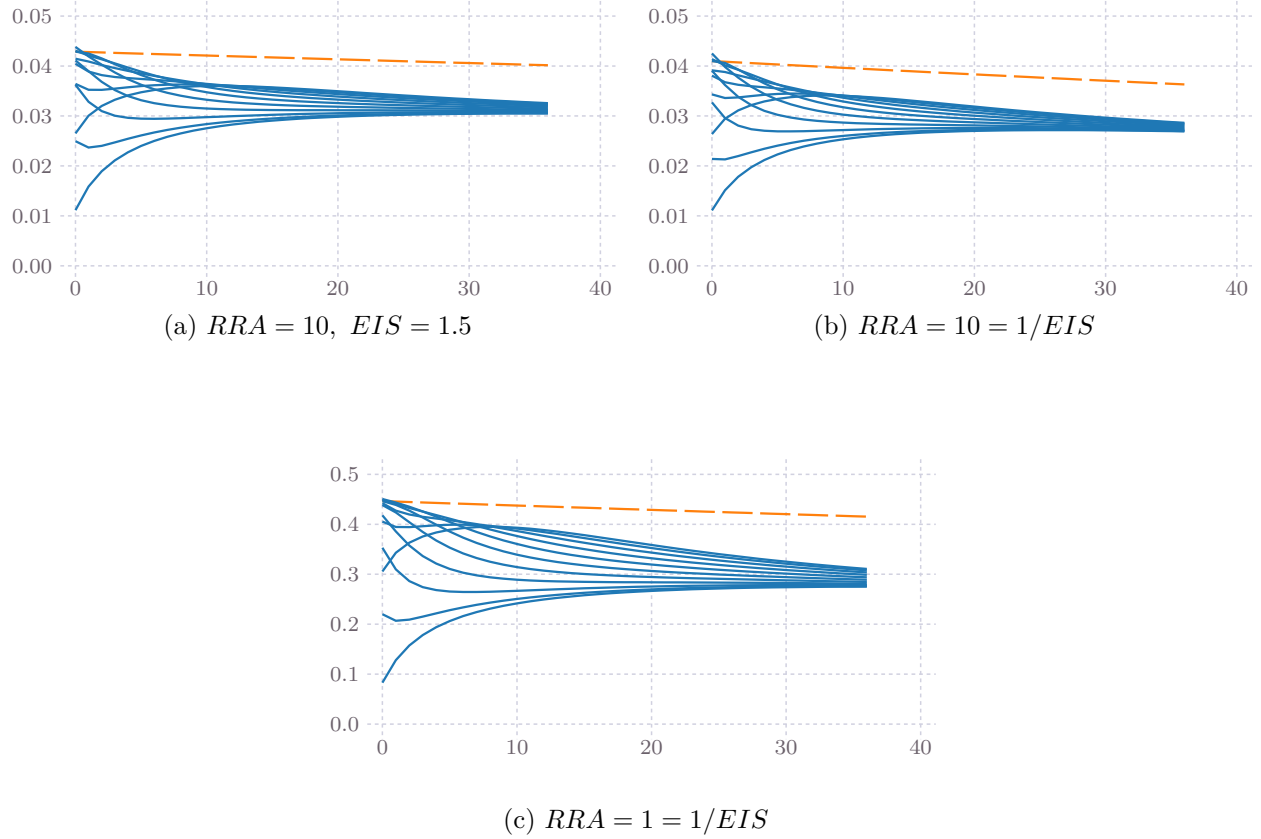


Figure 2: Value of One-time Information on Jobless Claims as function of its Delay

Plotted is the value of private information as a function of the delay of $\Delta \equiv t^* - t \geq 0$ periods between the time t that the information is acquired and the time t^* when a one-time signal on jobless claims is received. Each solid line is the value of information conditional on a different time- t state z_t . Higher lines correspond to worse states as the value of information is monotone decreasing in the S&P 500. The dashed lines are all decreasing in the delay because there we force the values of information at t^* in all states to be the same as those of the middle (current) state, effectively shutting down the interplay of delay with the state dependence of the value of information. Panel (a) reports results for the benchmark parameters: $\beta = 0.998$, $\gamma = 10$, $\rho = 1/1.5$, and $\tau = 1/12$ (Bansal and Yaron, 2004). Panel (b) is expected utility with $\gamma = \rho = 10$. Panel (c) is the log utility limiting case.

The second channel is that delayed information is discounted more heavily via a traditional time discount factor β , because the expected utility gain from the information occurs farther to the future. This channel is the dominant force for long delays, or if we shut down the first channel by eliminating the state dependence of the value of information (dashed line).

Our approach does omit a potential third channel by which delay could affect the value of information. One can imagine a delay between the time the signal is received and the time the state it is correlated with is realized. In our model this is hard wired to be exactly one period, i.e. the signal s_t is drawn from a conditional likelihood $\alpha(s_t|z_{t+1})$. Introducing a wedge Δ between them, such that $\alpha(s_t|z_{t+\Delta})$ is potentially interesting, but also complicates the analysis by introducing additional state variables. Intuitively, we expect such a wedge to decrease the value of information, but its formal analysis is left for future work.

D Limiting cases for the value of information

Here, for completeness, we provide results for some limiting cases of interest. The log value-to-consumption ratio for the no-information benchmark in state z_t depends on state priors $q(z_{t+1}|z_t)$ and natural transition probabilities $p(z_{t+1}|z_t)$ via the following recursions:

$$v(z_t) \equiv \log \frac{V}{c} = \begin{cases} \frac{1}{1-\rho} \log \left\{ 1 - \beta + \beta^{\frac{1}{\rho}} \left[\sum_{z_{t+1}} \left\{ q(z_{t+1}|z_t)^{\gamma-1} e^{(1-\gamma)\rho v(z_{t+1})} p(z_{t+1}|z_t) \right\}^{\frac{1}{\gamma}} \right]^{\frac{\gamma}{\rho} \frac{1-\rho}{1-\gamma}} \right\} & \text{if } \rho \neq 1, \gamma > 1 \\ \frac{1}{1-\gamma} \log \left\{ 1 - \beta + \beta^{\frac{1}{\gamma}} \left[\sum_{z_{t+1}} \left\{ q(z_{t+1}|z_t)^{\gamma-1} e^{(1-\gamma)\gamma v(z_{t+1})} p(z_{t+1}|z_t) \right\}^{\frac{1}{\gamma}} \right] \right\} & \text{if } \rho = \gamma \neq 1 \\ \frac{1}{1-\rho} \log \left\{ 1 - \beta + \beta^{\frac{1}{\rho}} \exp \left(\frac{1-\rho}{\rho} \sum_{z_{t+1}} \left[\log \frac{p(z_{t+1}|z_t)}{q(z_{t+1}|z_t)} + \rho v(z_{t+1}) \right] p(z_{t+1}|z_t) \right) \right\} & \text{if } \rho \neq 1, \gamma = 1 \\ \beta \log \beta + \frac{\beta\gamma}{1-\gamma} \log \left[\sum_{z_{t+1}} \left\{ q(z_{t+1}|z_t)^{\gamma-1} e^{(1-\gamma)v(z_{t+1})} p(z_{t+1}|z_t) \right\}^{\frac{1}{\gamma}} \right] & \text{if } \rho = 1, \gamma > 1 \\ \beta \log \beta + \beta \sum_{z_{t+1}} \left\{ \log \frac{p(z_{t+1}|z_t)}{q(z_{t+1}|z_t)} + v(z_{t+1}) \right\} p(z_{t+1}|z_t) & \text{if } \rho = \gamma = 1. \end{cases} \quad (17)$$

The corresponding equations given a signal s_t from information source α are

$$v(z_t, s_t) = \begin{cases} \left[\frac{1}{1-\rho} \log \left\{ 1 - \beta + \beta^{\frac{1}{\rho}} \left[\sum_{z_{t+1}} \left\{ q(z_{t+1}|z_t)^{\gamma-1} E \left[e^{(1-\gamma)\rho v(z_{t+1}, s_{t+1})} | z_{t+1} \right] p_{\alpha}(z_{t+1}|z_t, s_t) \right\}^{\frac{1}{\gamma}} \right]^{\frac{\gamma}{\rho} \frac{1-\rho}{1-\gamma}} \right\} \right]^{\frac{\gamma}{\rho} \frac{1-\rho}{1-\gamma}} & \text{if } \rho \neq 1, \gamma > 1 \\ \frac{1}{1-\gamma} \log \left\{ 1 - \beta + \beta^{\frac{1}{\gamma}} \left[\sum_{z_{t+1}} \left\{ q(z_{t+1}|z_t)^{\gamma-1} E \left[e^{(1-\gamma)\gamma v(z_{t+1}, s_{t+1})} | z_{t+1} \right] p_{\alpha}(z_{t+1}|z_t, s_t) \right\}^{\frac{1}{\gamma}} \right] \right\} & \text{if } \rho = \gamma \neq 1 \\ \frac{1}{1-\rho} \log \left\{ 1 - \beta + \beta^{\frac{1}{\rho}} \exp \left(\frac{1-\rho}{\rho} \sum_{z_{t+1}} \left[\log \frac{p_{\alpha}(z_{t+1}|z_t, s_t)}{q(z_{t+1}|z_t)} + E[\rho v(z_{t+1}, s_{t+1}; \alpha) | z_{t+1}] \right] p_{\alpha}(z_{t+1}|z_t, s_t) \right) \right\} & \text{if } \rho \neq 1, \gamma = 1 \\ \beta \log \beta + \frac{\beta\gamma}{1-\gamma} \log \left[\sum_{z_{t+1}} \left\{ q(z_{t+1}|z_t)^{\gamma-1} E \left[e^{(1-\gamma)v(z_{t+1}, s_{t+1}; \alpha)} | z_{t+1} \right] p_{\alpha}(z_{t+1}|z_t, s_t) \right\}^{\frac{1}{\gamma}} \right] & \text{if } \rho = 1, \gamma > 1 \\ \beta \log \beta + \beta \sum_{z_{t+1}} \left\{ \log \frac{p_{\alpha}(z_{t+1}|z_t, s_t)}{q(z_{t+1}|z_t)} + E[v(z_{t+1}, s_{t+1}) | z_{t+1}] \right\} p_{\alpha}(z_{t+1}|z_t, s_t) & \text{if } \rho = \gamma = 1. \end{cases} \quad (18)$$

Limiting cases of the value of information moments (36) are

$$f_i(\omega; x_t) = \begin{cases} e^{(\gamma-1)[\rho v_{it}(\alpha_0) + \omega_i]} \left\{ 1 - \beta + \beta^{\frac{1}{\rho}} \Gamma_{it}^{\frac{\gamma(1-\rho)}{\rho(1-\gamma)}} \right\}^{\frac{\rho(1-\gamma)}{1-\rho}} - 1 & \text{if } \rho \neq 1, \gamma > 1 \\ e^{(\gamma-1)[\gamma v_{it}(\alpha_0) + \omega_i]} \left\{ 1 - \beta + \beta^{\frac{1}{\gamma}} \Gamma_{it} \right\}^{\gamma} - 1 & \text{if } \rho = \gamma \neq 1 \\ \frac{\rho}{1-\rho} \log \left\{ 1 - \beta + \beta^{\frac{1}{\rho}} \exp \left(\frac{1-\rho}{\rho} \Gamma_{it} \right) \right\} - \rho v_{it}(\alpha_0) - \omega_i & \text{if } \rho \neq 1, \gamma = 1 \\ e^{(\gamma-1)[v_{it}(\alpha_0) + \omega_i]} \beta^{\beta(1-\gamma)} \Gamma_{it}^{\beta\gamma} - 1 & \text{if } \rho = 1, \gamma > 1 \\ \beta \log \beta + \beta \Gamma_{it} - v_{it}(\alpha_0) - \omega_i & \text{if } \rho = \gamma = 1, \end{cases} \quad (19)$$

where

$$\Gamma_{it} = \begin{cases} \sum_k p_{ikt}^* e^{\frac{1-\gamma}{\gamma} [\rho v_{kt}(\alpha_0) + \omega_k + \log(p_{ikt}^*/q_{ikt})]} & \text{if } \gamma > 1 \\ \sum_k p_{ikt}^* [\rho v_{kt}(\alpha_0) + \omega_k + \log(p_{ikt}^*/q_{ikt})] & \text{if } \gamma = 1. \end{cases} \quad (20)$$

E Comparative statics for all macroeconomic events

To conserve space, in the paper we report comparative statics figures only for jobless claims reports, because they are qualitatively quite similar for other studied events. Below we report comparative statics figures for all macroeconomic events, organized by the varied parameter to facilitate comparison.

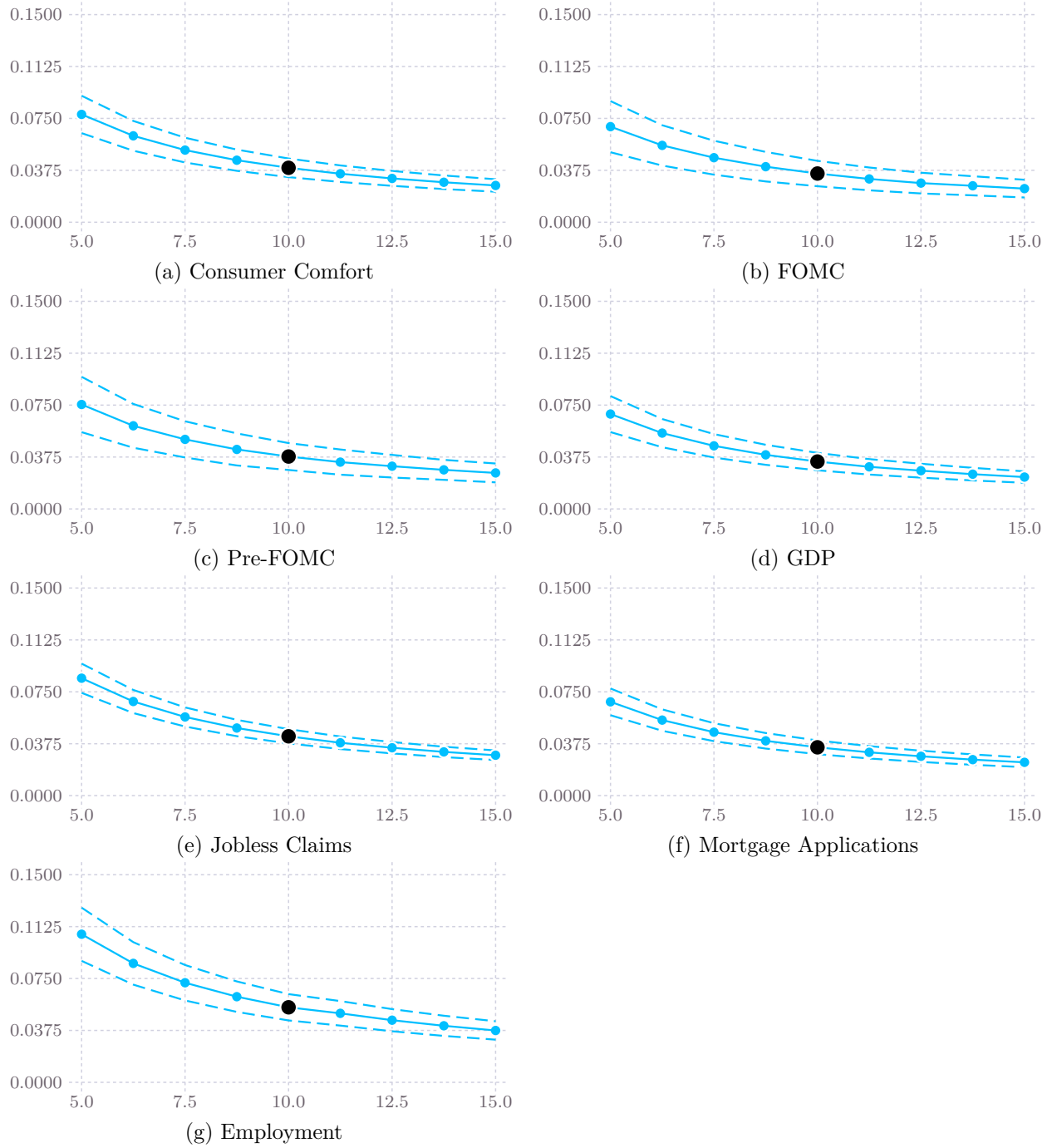


Figure 3: Value of a *one-time signal* as a function of the *relative risk aversion* γ . Plotted are comparative statics of the value of private information as percent of wealth around our benchmark parameters: $\beta = 0.998$, $\gamma = 10$, $\rho = 1/1.5$, and $\tau = 1/12$ (Bansal and Yaron, 2004). The benchmark estimate is circled in each plot. Dashed lines are the 95 percent confidence interval using Newey-West standard errors with two lags. The value of a one-time signal is on the left and that of a signal every period is on the right.

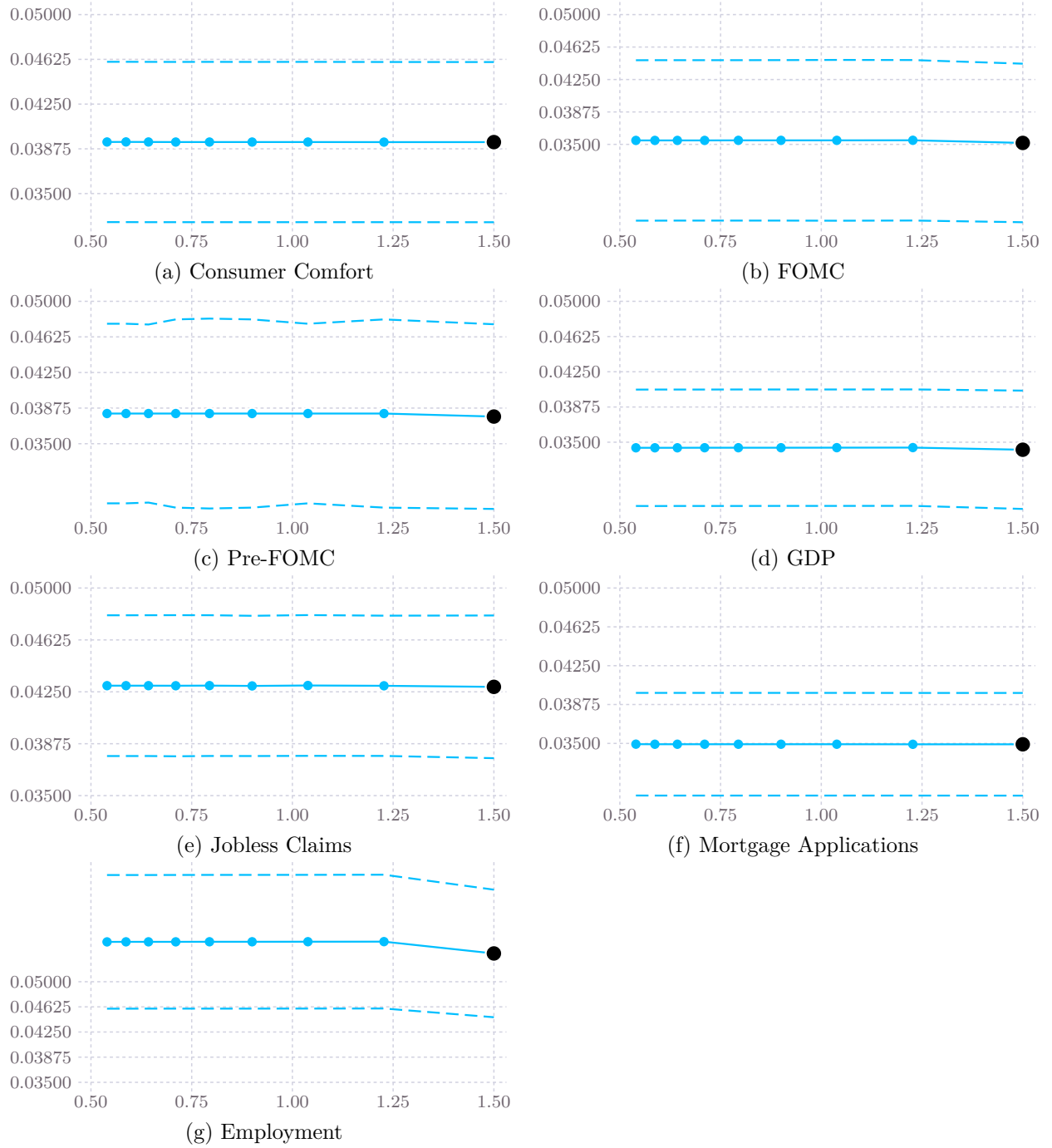


Figure 4: Value of a *one-time signal* as a function of the *elasticity of intertemporal substitution* $1/\rho$. Plotted are comparative statics of the value of private information as percent of wealth around our benchmark parameters: $\beta = 0.998$, $\gamma = 10$, $\rho = 1/1.5$, and $\tau = 1/12$ (Bansal and Yaron, 2004). The benchmark estimate is circled in each plot. Dashed lines are the 95 percent confidence interval using Newey-West standard errors with two lags. The value of a one-time signal is on the left and that of a signal every period is on the right.



Figure 5: Value of a *one-time signal* as a function of the *time discount factor* β . Plotted are comparative statics of the value of private information as percent of wealth around our benchmark parameters: $\beta = 0.998$, $\gamma = 10$, $\rho = 1/1.5$, and $\tau = 1/12$ (Bansal and Yaron, 2004). The benchmark estimate is circled in each plot. Dashed lines are the 95 percent confidence interval using Newey-West standard errors with two lags. The value of a one-time signal is on the left and that of a signal every period is on the right.

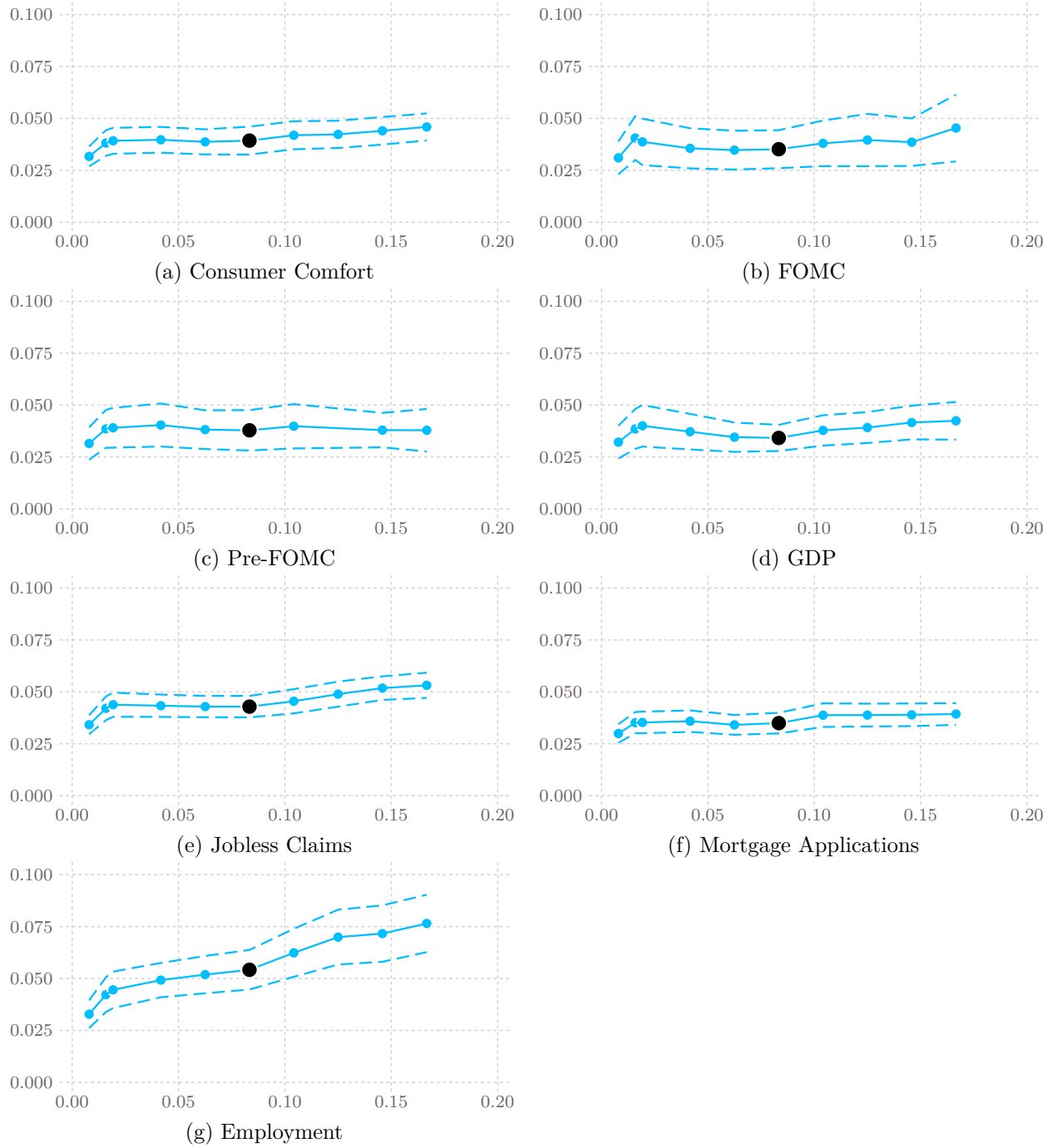


Figure 6: Value of a *one-time signal* as a function of the *horizon in years*
Plotted are comparative statics of the value of private information as percent of wealth around our benchmark parameters: $\beta = 0.998$, $\gamma = 10$, $\rho = 1/1.5$, and $\tau = 1/12$ (Bansal and Yaron, 2004). The benchmark estimate is circled in each plot. Dashed lines are the 95 percent confidence interval using Newey-West standard errors with two lags. The value of a one-time signal is on the left and that of a signal every period is on the right.

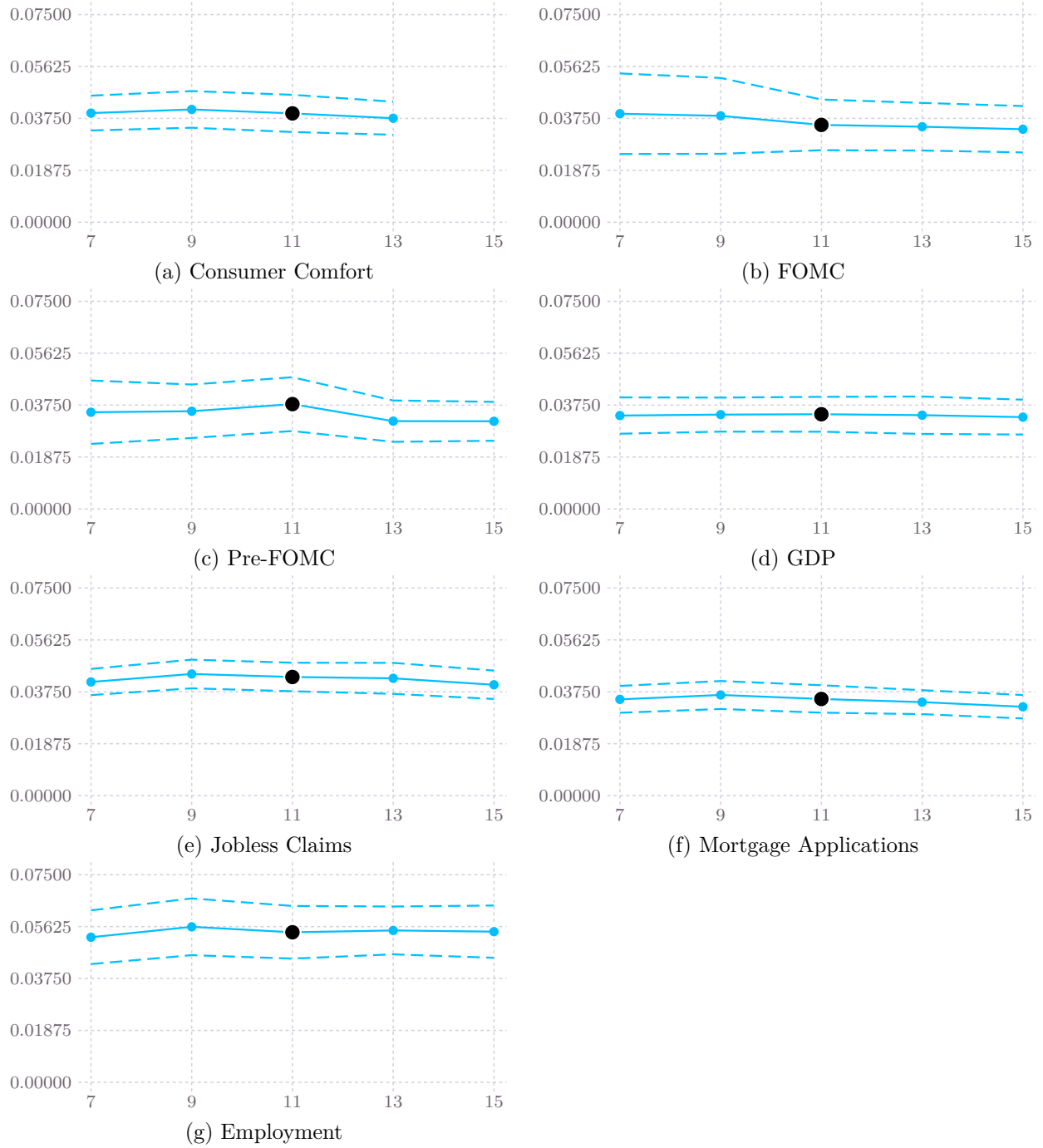


Figure 7: Value of a *one-time signal* as a function of the *number of states* n . Plotted are comparative statics of the value of private information as percent of wealth around our benchmark parameters: $\beta = 0.998$, $\gamma = 10$, $\rho = 1/1.5$, and $\tau = 1/12$ (Bansal and Yaron, 2004). The benchmark estimate is circled in each plot. Dashed lines are the 95 percent confidence interval using Newey-West standard errors with two lags. The value of a one-time signal is on the left and that of a signal every period is on the right.



Figure 8: Value of a *one-time signal* as a function of the *state spacing* dk . Plotted are comparative statics of the value of private information as percent of wealth around our benchmark parameters: $\beta = 0.998$, $\gamma = 10$, $\rho = 1/1.5$, and $\tau = 1/12$ (Bansal and Yaron, 2004). The benchmark estimate is circled in each plot. Dashed lines are the 95 percent confidence interval using Newey-West standard errors with two lags. The value of a one-time signal is on the left and that of a signal every period is on the right.

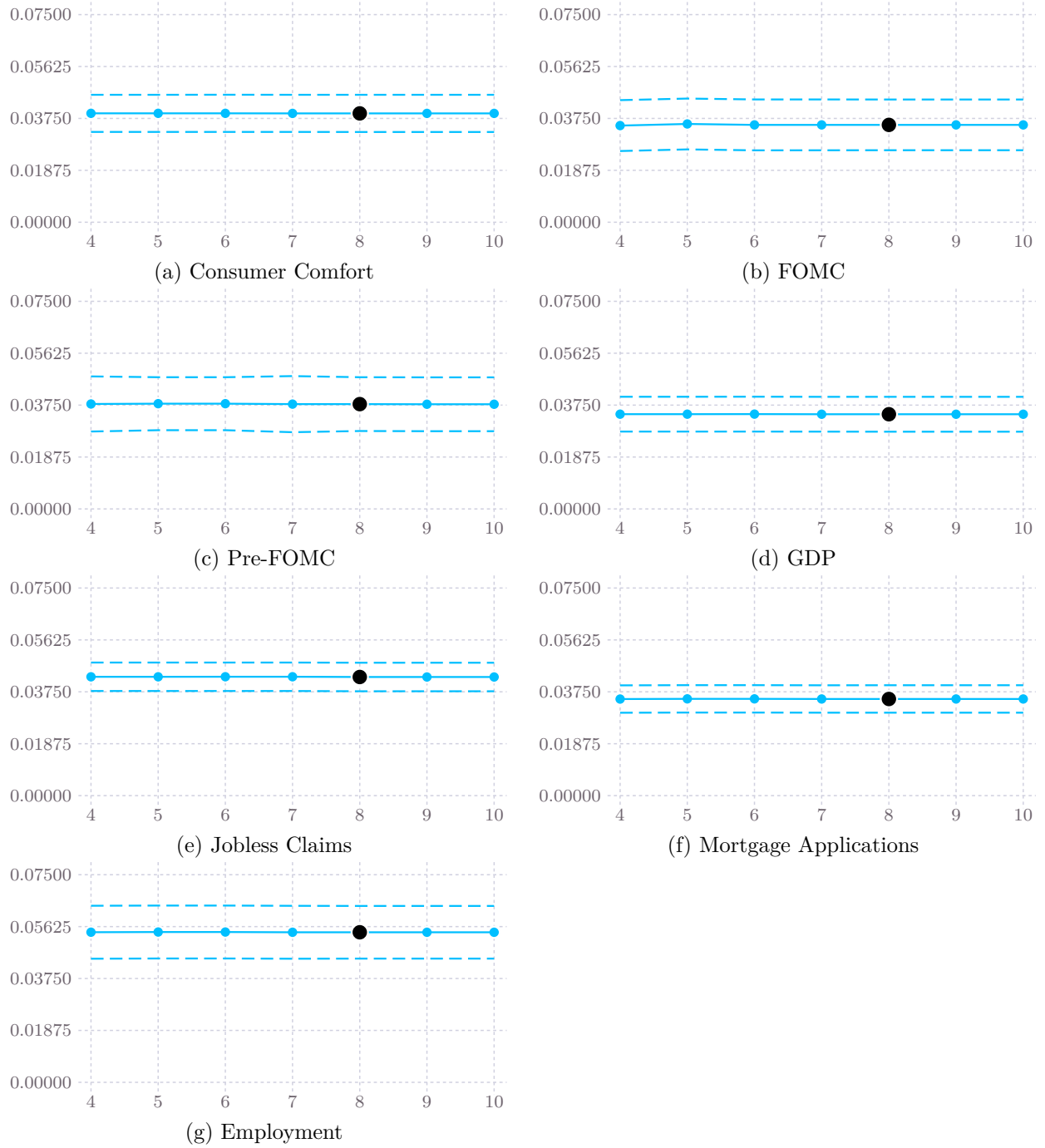


Figure 9: Value of a *one-time signal* as a function of the *optimization precision*. Plotted are comparative statics of the value of private information as percent of wealth around our benchmark parameters: $\beta = 0.998$, $\gamma = 10$, $\rho = 1/1.5$, and $\tau = 1/12$ (Bansal and Yaron, 2004). The benchmark estimate is circled in each plot. Dashed lines are the 95 percent confidence interval using Newey-West standard errors with two lags. The value of a one-time signal is on the left and that of a signal every period is on the right.

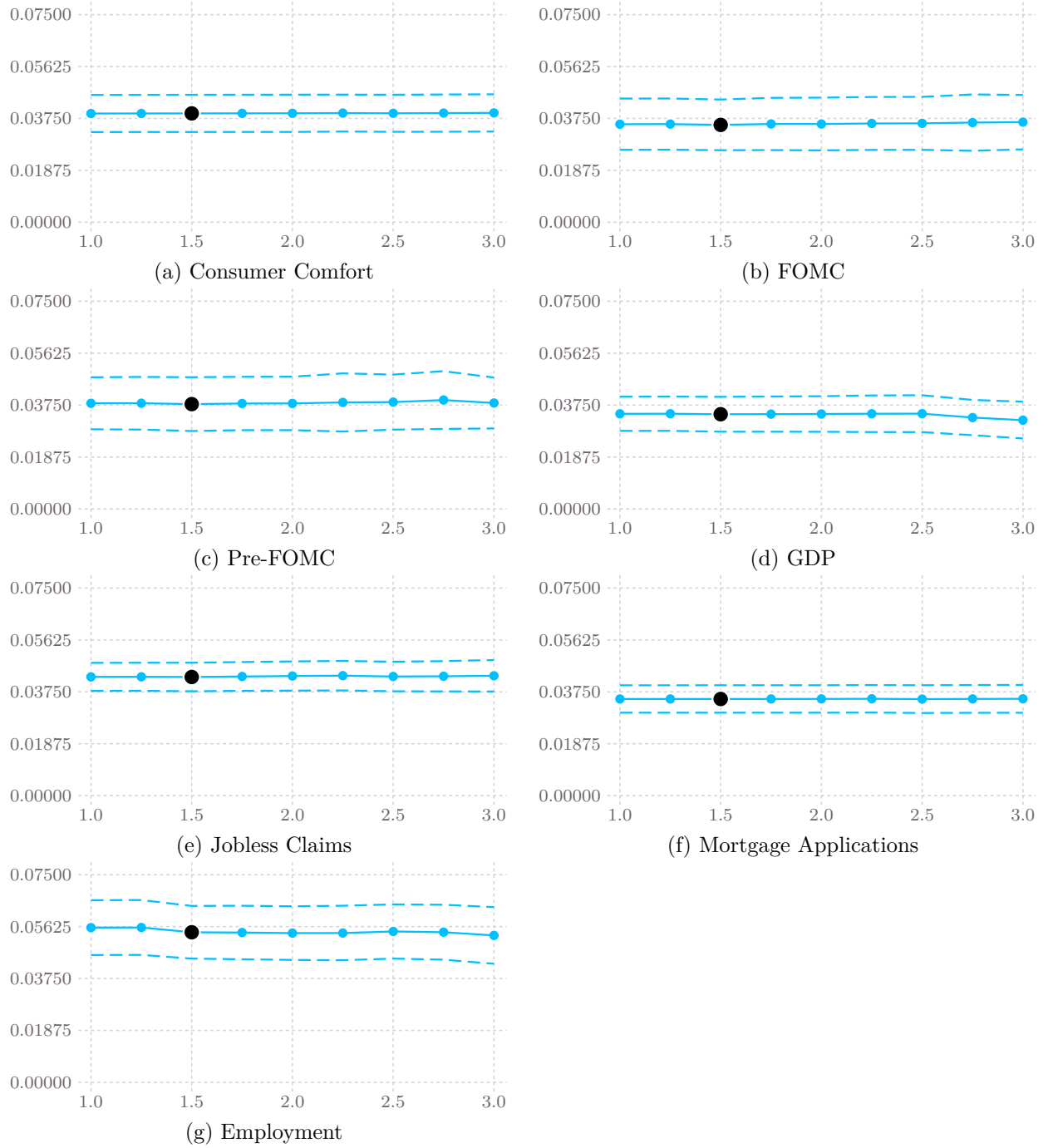


Figure 10: Value of a *one-time signal* as a function of the *SDF exponent* ϵ . Plotted are comparative statics of the value of private information as percent of wealth around our benchmark parameters: $\beta = 0.998$, $\gamma = 10$, $\rho = 1/1.5$, and $\tau = 1/12$ (Bansal and Yaron, 2004). The benchmark estimate is circled in each plot. Dashed lines are the 95 percent confidence interval using Newey-West standard errors with two lags. The value of a one-time signal is on the left and that of a signal every period is on the right.

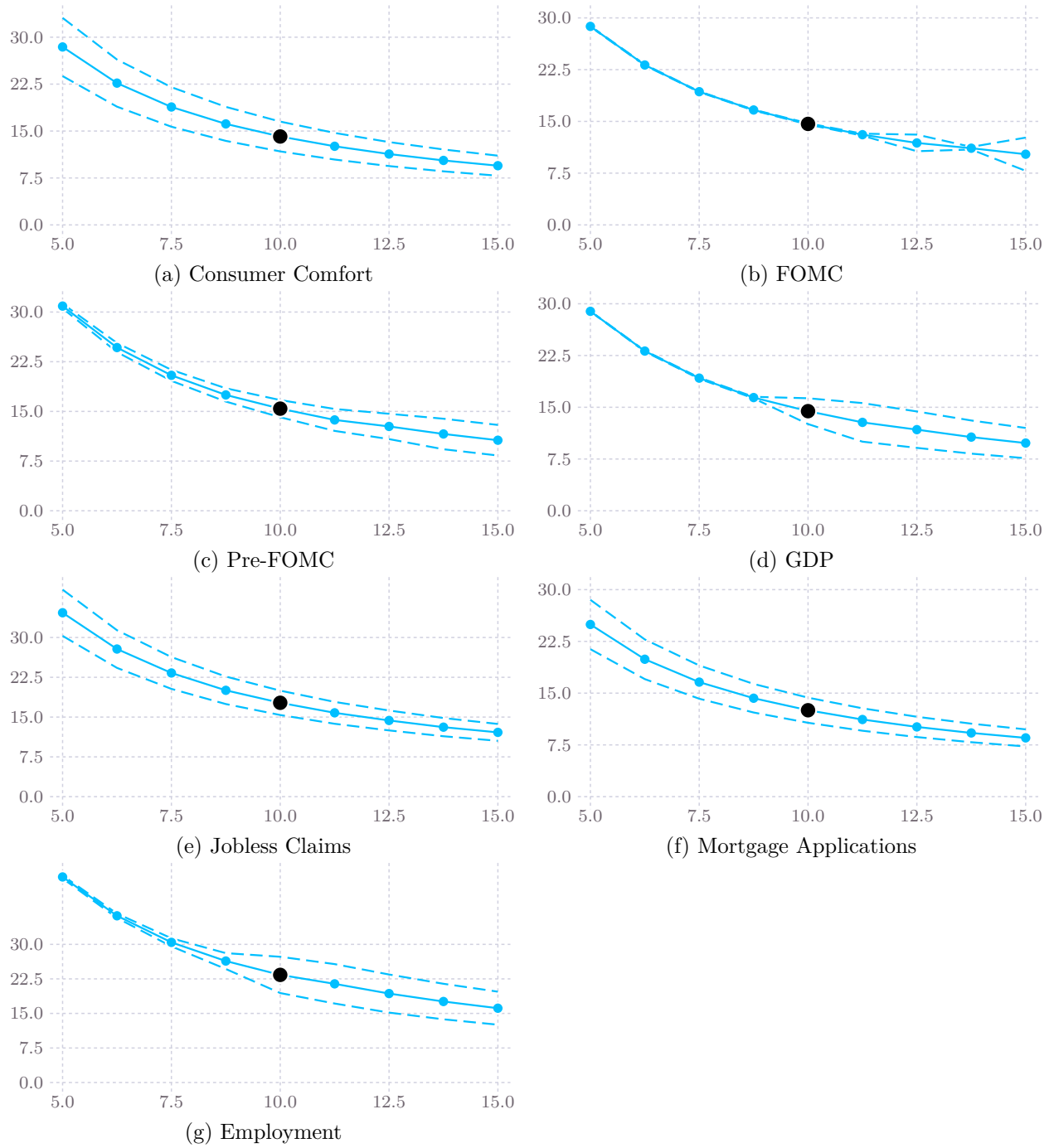


Figure 11: Value of a *signal every period* as a function of the *relative risk aversion* γ . Plotted are comparative statics of the value of private information as percent of wealth around our benchmark parameters: $\beta = 0.998$, $\gamma = 10$, $\rho = 1/1.5$, and $\tau = 1/12$ (Bansal and Yaron, 2004). The benchmark estimate is circled in each plot. Dashed lines are the 95 percent confidence interval using Newey-West standard errors with two lags. The value of a one-time signal is on the left and that of a signal every period is on the right.

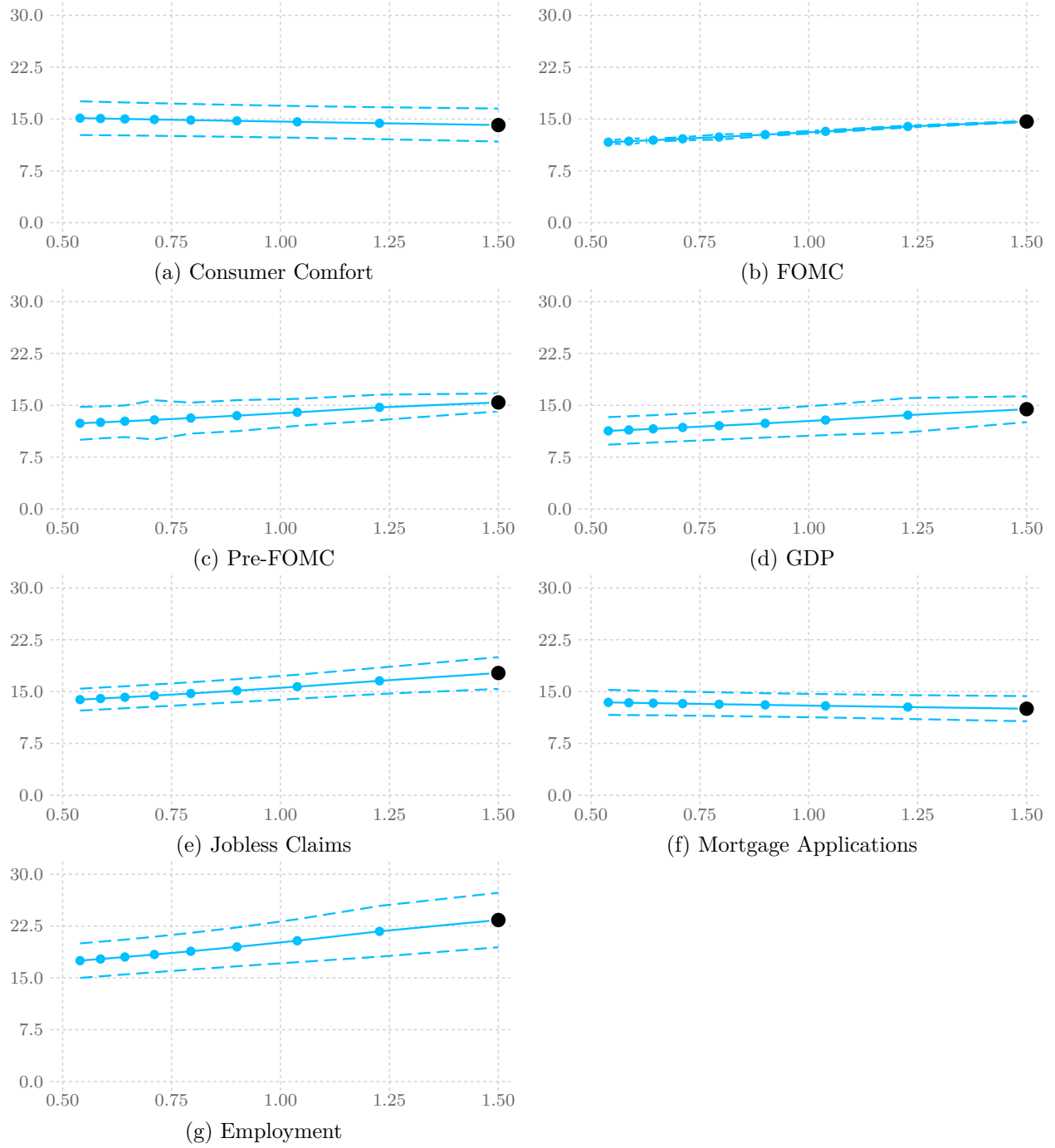


Figure 12: Value of a *signal every period* as a function of the *elasticity of intertemporal substitution* $1/\rho$

Plotted are comparative statics of the value of private information as percent of wealth around our benchmark parameters: $\beta = 0.998$, $\gamma = 10$, $\rho = 1/1.5$, and $\tau = 1/12$ (Bansal and Yaron, 2004). The benchmark estimate is circled in each plot. Dashed lines are the 95 percent confidence interval using Newey-West standard errors with two lags. The value of a one-time signal is on the left and that of a signal every period is on the right.

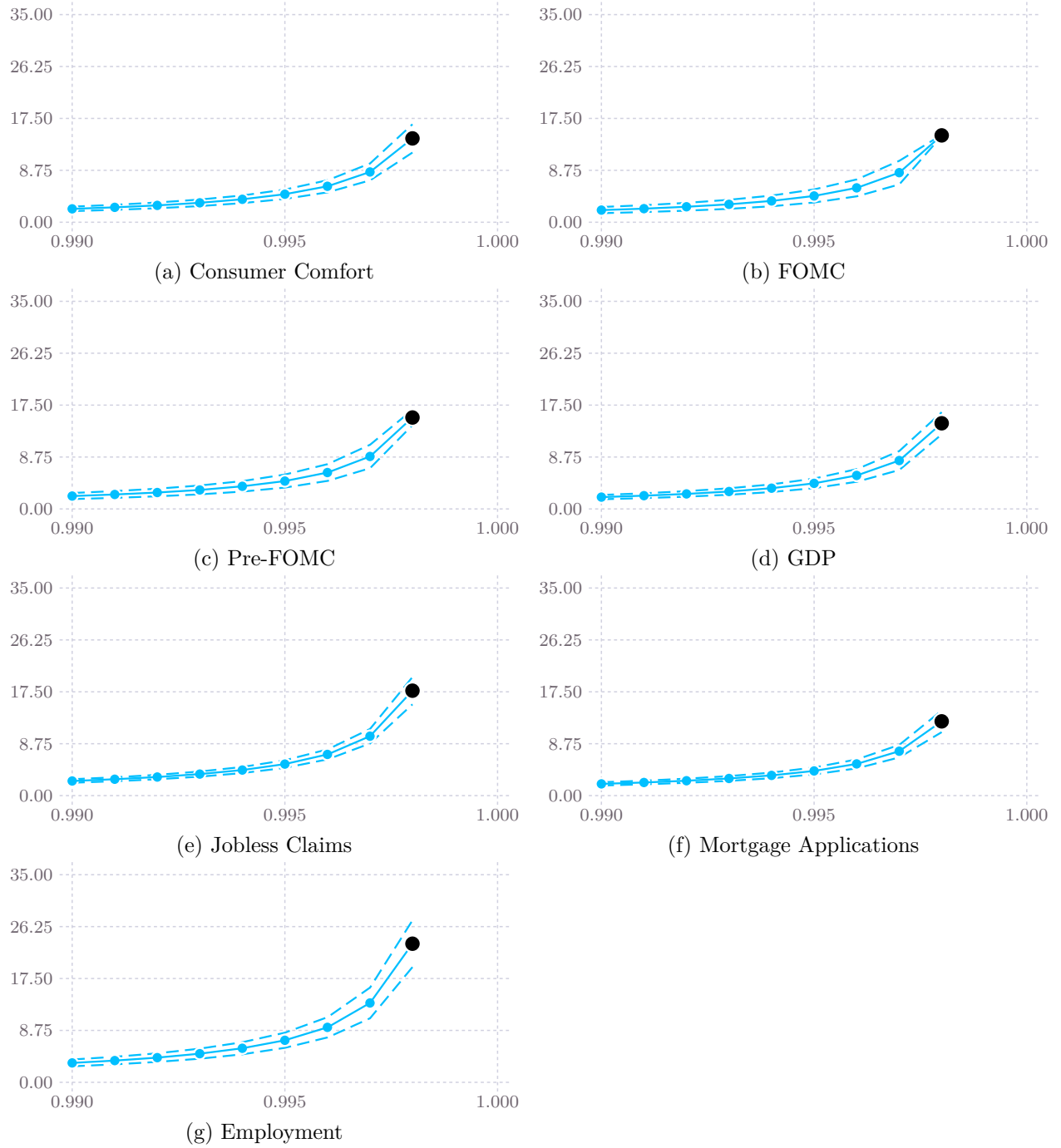


Figure 13: Value of a *signal every period* as a function of the *time discount factor* β . Plotted are comparative statics of the value of private information as percent of wealth around our benchmark parameters: $\beta = 0.998$, $\gamma = 10$, $\rho = 1/1.5$, and $\tau = 1/12$ (Bansal and Yaron, 2004). The benchmark estimate is circled in each plot. Dashed lines are the 95 percent confidence interval using Newey-West standard errors with two lags. The value of a one-time signal is on the left and that of a signal every period is on the right.

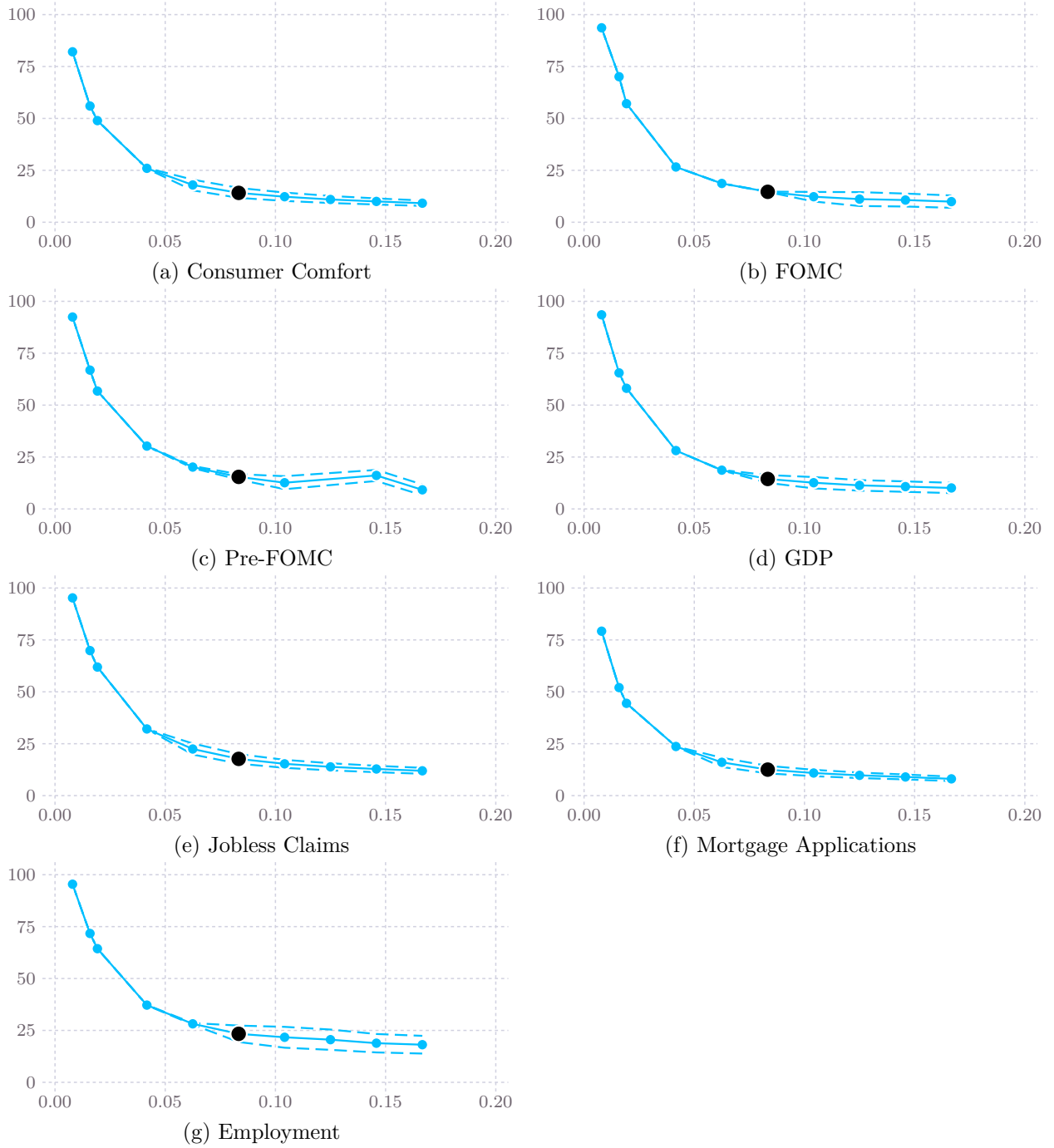


Figure 14: Value of a *signal every period* as a function of the *horizon in years*
 Plotted are comparative statics of the value of private information as percent of wealth around our benchmark parameters: $\beta = 0.998$, $\gamma = 10$, $\rho = 1/1.5$, and $\tau = 1/12$ (Bansal and Yaron, 2004). The benchmark estimate is circled in each plot. Dashed lines are the 95 percent confidence interval using Newey-West standard errors with two lags. The value of a one-time signal is on the left and that of a signal every period is on the right.

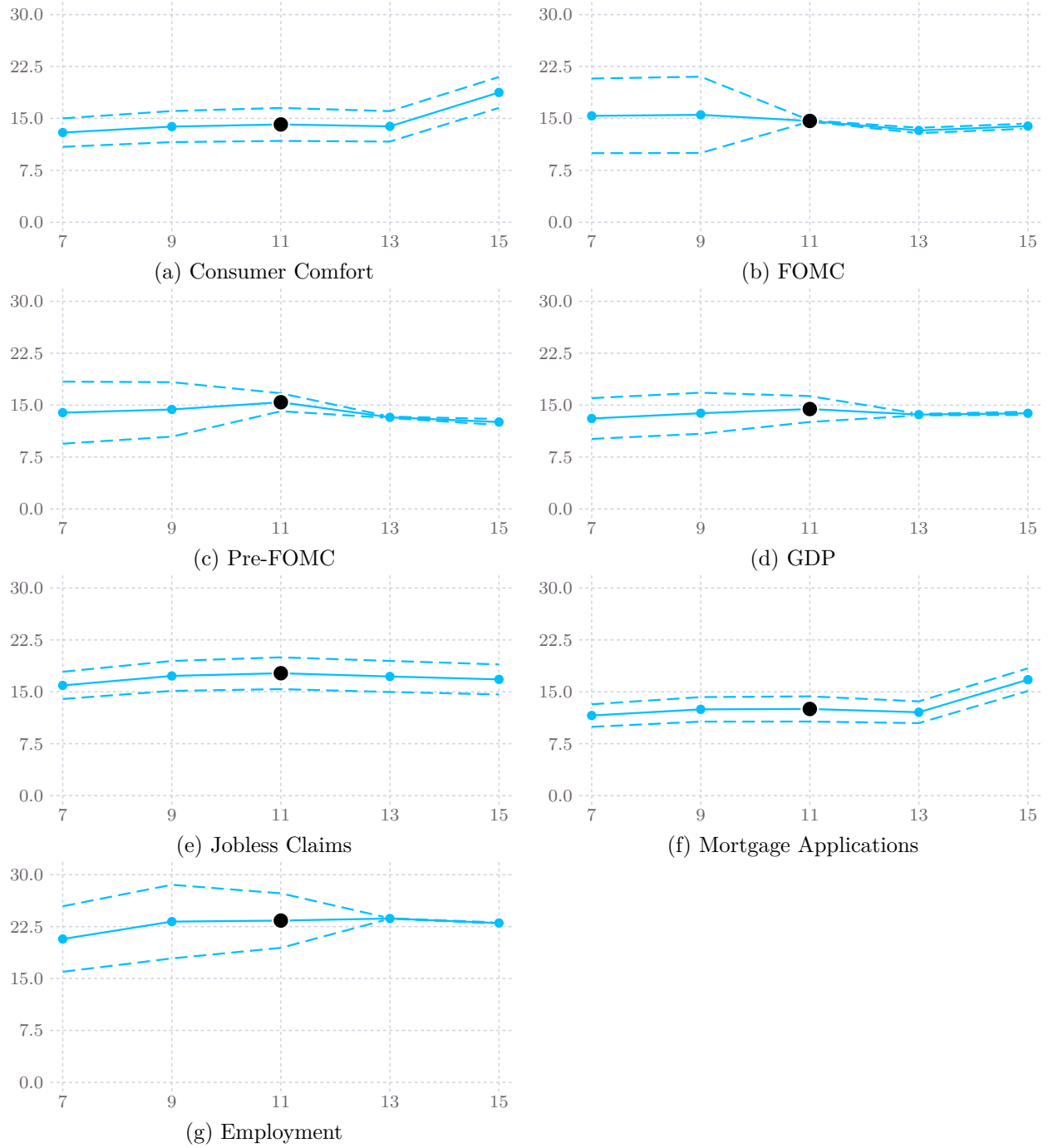


Figure 15: Value of a *signal every period* as a function of the *number of states* n . Plotted are comparative statics of the value of private information as percent of wealth around our benchmark parameters: $\beta = 0.998$, $\gamma = 10$, $\rho = 1/1.5$, and $\tau = 1/12$ (Bansal and Yaron, 2004). The benchmark estimate is circled in each plot. Dashed lines are the 95 percent confidence interval using Newey-West standard errors with two lags. The value of a one-time signal is on the left and that of a signal every period is on the right.

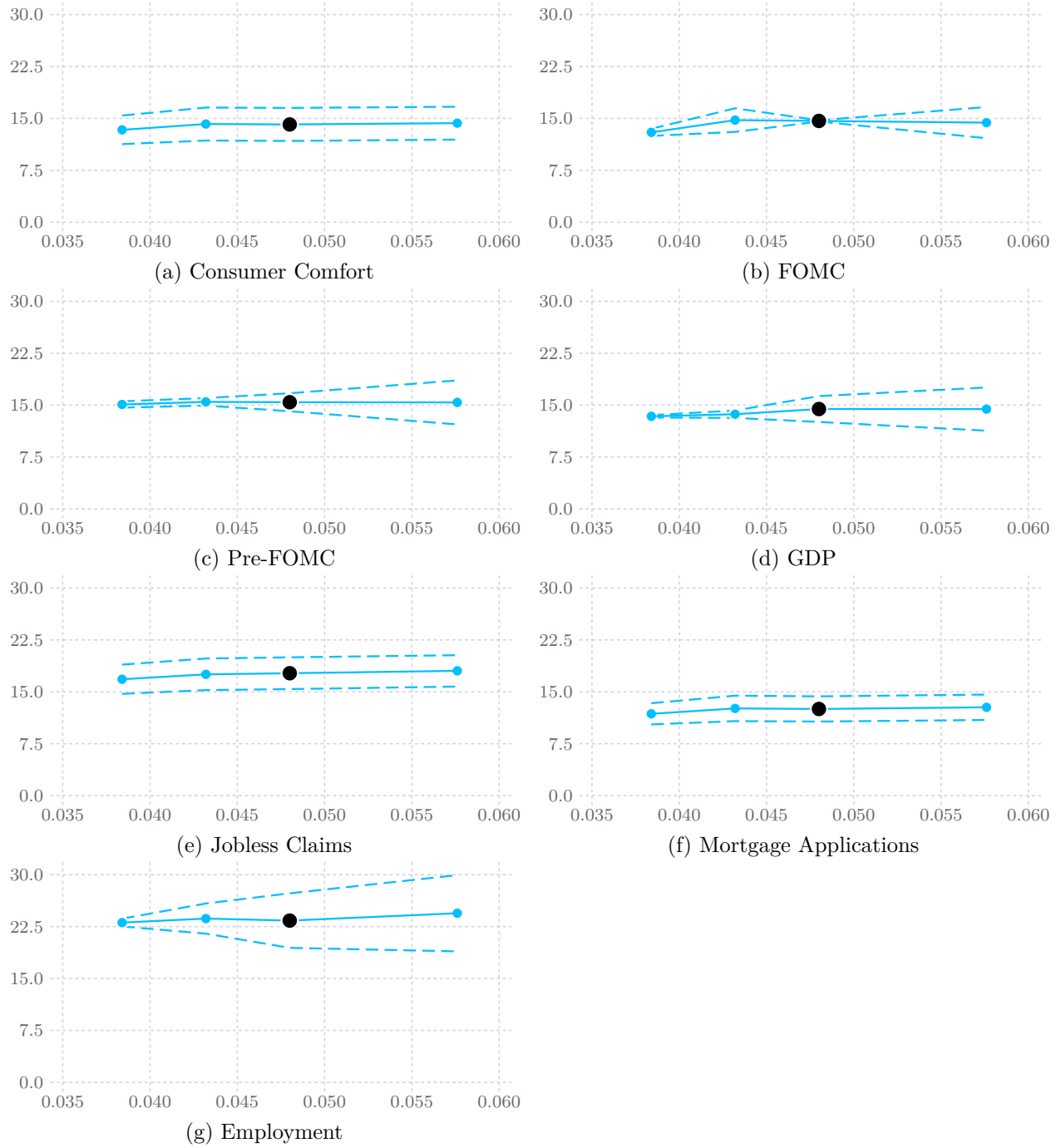


Figure 16: Value of a *signal every period* as a function of the *state spacing* dk . Plotted are comparative statics of the value of private information as percent of wealth around our benchmark parameters: $\beta = 0.998$, $\gamma = 10$, $\rho = 1/1.5$, and $\tau = 1/12$ (Bansal and Yaron, 2004). The benchmark estimate is circled in each plot. Dashed lines are the 95 percent confidence interval using Newey-West standard errors with two lags. The value of a one-time signal is on the left and that of a signal every period is on the right.

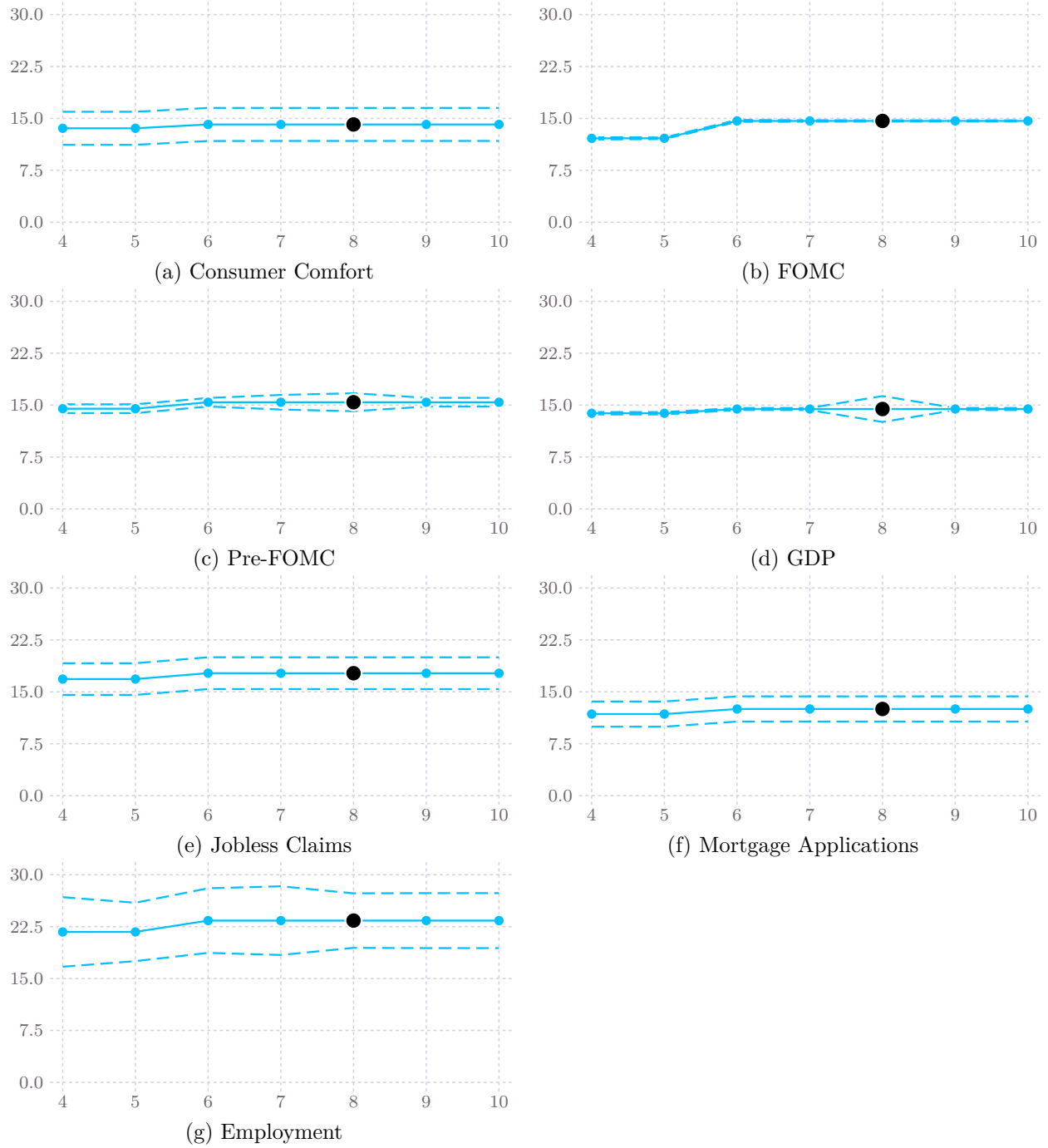


Figure 17: Value of a *signal every period* as a function of the *optimization precision*. Plotted are comparative statics of the value of private information as percent of wealth around our benchmark parameters: $\beta = 0.998$, $\gamma = 10$, $\rho = 1/1.5$, and $\tau = 1/12$ (Bansal and Yaron, 2004). The benchmark estimate is circled in each plot. Dashed lines are the 95 percent confidence interval using Newey-West standard errors with two lags. The value of a one-time signal is on the left and that of a signal every period is on the right.

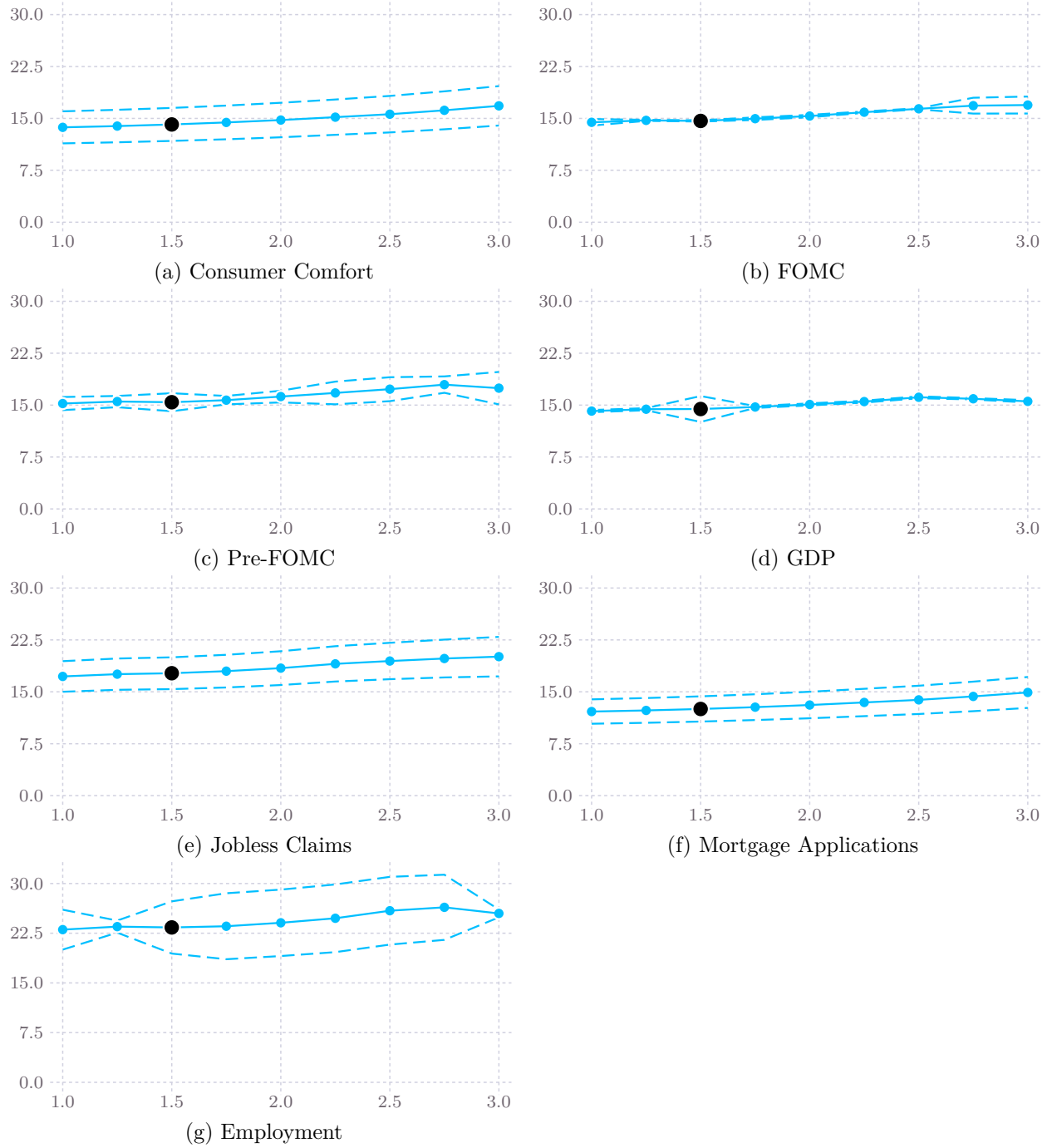


Figure 18: Value of a *signal every period* as a function of the *SDF exponent* ϵ . Plotted are comparative statics of the value of private information as percent of wealth around our benchmark parameters: $\beta = 0.998$, $\gamma = 10$, $\rho = 1/1.5$, and $\tau = 1/12$ (Bansal and Yaron, 2004). The benchmark estimate is circled in each plot. Dashed lines are the 95 percent confidence interval using Newey-West standard errors with two lags. The value of a one-time signal is on the left and that of a signal every period is on the right.

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