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"Optimal Unemployment Insurance with Monitoring"

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Abstract

I study a principal-agent problem in which the principal can obtain additional costly information about the agent's effort. I analyze this problem in the context of optimal unemployment insurance a la Hopenhayn and Nicolini (1997), where job-search effort is private information. I calibrate the model to the US economy and use it for two purposes. First, I show that for CRRA utility, the optimal contract dictates that monitoring frequency increases and the sanction decreases with promised utility, if and only if the coefficient of risk aversion is greater than 0.5. Second, I show that compared to optimal unemployment insurance and estimated at the balanced budget point, monitoring saves about eighty percent of the cost associated with moral hazard.

1 Introduction

Most unemployment insurance programs in the United States include monitoring of job-search effort (Grubb, 2000). A typical monitoring policy requires the unemployed worker to record her job-search activities by listing the employers she contacted in a given period. At the employment office, a caseworker occasionally evaluates whether the job-search requirements are met by verifying that the contacts are authentic. If the caseworker finds the report unsatisfactory, then she may impose sanctions, usually in the form of a reduction in benefits for a limited period.[1]

In this paper I incorporate *monitoring* into the principal-agent framework of *optimal unemployment insurance* developed by Hopenhayn and Nicolini (1997). Monitoring allows the principal (planner) to acquire a costly imperfect signal that is used in the contract. I calibrate the model to the US economy and use it for two purposes. First, I show how the planner combines the monitoring frequency with sanctions and rewards as a function of the labor market history of the worker. Second, I assess the effectiveness of monitoring by estimating the fraction of moral hazard cost that is saved when monitoring is used.

In optimal unemployment insurance, a risk-neutral planner insures a risk-averse worker against unemployment by setting transfers during unemployment and a wage tax or a subsidy during employment. During unemployment, the worker searches for a job by exerting effort, the level of which is her private information. Since the planner cannot observe the job-search effort, the constant benefits that are implied by the first-best contract would undermine the worker's incentives to search for a job. Therefore, to solve the incentive-insurance trade-off, benefits should continuously decrease during unemployment and the wage tax upon re-employment should continuously increase.

I include monitoring in this framework as follows. The planner monitors the unem-

[1] Other countries (e.g., Australia, Canada, Switzerland and the United Kingdom) use job-search monitoring for unemployed workers as well (Grubb, 2000). Since the activity characteristics defer across countries, I focus in this paper on the implementation of job-search monitoring in the United States.

ployed worker at some history-dependent frequency. When a worker is monitored, the planner pays a cost and receives a signal that is correlated with the worker's job-search effort. The planner uses that signal to improve the efficiency of the contract by conditioning future payments and the wage tax not only on the employment outcome, but also on the signal. These future payments create endogenous sanctions and rewards that, together with the random monitoring, create effective job-search incentives. The worker exerts a high job-search effort in order to increase the probability of a good signal and, consequently, increase the probability of higher payments.

I characterize the optimal contract using a calibration of the model to the US economy for a worker with logarithmic utility from consumption. The monitoring frequency and the dispersion of future utilities complement one another in creating the incentives for the worker to search actively for a job. The specific combination of those two components depends on promised utility, which represents the welfare system's generosity. As the generosity of the welfare system increases, the planner monitors the unemployed worker more frequently but imposes lower sanctions. The driving force of this result is that while the per-unit cost of monitoring is independent of the generosity of the welfare system, as I show below the cost of spreading out future utilities increases with generosity.

In Appendix A, I describe a two-period model that captures the same economic forces as the infinite-horizon model. Specifically, the possible outcomes, their probabilities, and the choice variables of the planner are all identical to the infinite-horizon model. The theoretical solution to this model is consistent with the description of the results above. These results are carried to any parametrization of the model as long as the utility from consumption is logarithmic.

I then show that the characteristics of the optimal contract continue to hold in the infinite-horizon model for any CRRA preferences with a coefficient of risk aversion σ of at least 0.5. When $\sigma < 0.5$ the exact opposite happens: As the generosity increases, the monitoring frequency decreases and the spread between future utilities (henceforth, spreads) increases. This happens because $\sigma = 0.5$ is the cutoff point between spreading costs that increase with generosity ($\sigma > 0.5$) and spreading costs that decrease with generosity.

The calibrated model is also used for estimating the value of monitoring by comparing the results of this model to those of a model where monitoring technology is unavailable. Keeping utility fixed, I compare the gain from monitoring to the gain from shifting to the first-best allocation. This comparison is conducted at the generosity level that balances the government budget when applying the model with no monitoring. I find that the gain from monitoring equals roughly 80% of the difference between the planner's value of the first best and the value in the model without monitoring. These savings stem from the planner's ability to smooth the worker's consumption across states. Indeed, monitoring decreases about half the standard deviation of consumption.

The remainder of the paper is organized as follows. In Section 2, I describe the relevant literature. In Section 3, I describe the model. In Section 4, I calibrate the model to the US economy. In Section 5, I characterize the optimal monitoring policy and estimate the value of monitoring. In Section 6, I conclude and discuss further research.

2 Literature review

A typical assumption in principal-agent models that include costly state verification is that monitoring perfectly reveals the agent's hidden information (or action) to the principal.[2] In a standard environment, such signals allow the planner to get arbitrarily close to the first-best allocation, by using a combination of very low monitoring frequencies (that cost very little) with extremely severe punishments that will never be applied.[3]

[2] This simplifying assumption rests on Becker (1968) seminal paper "Crime and Punishment".

[3] In practice, it may be infeasible to perfectly verify the level of the worker's job-search effort. Furthermore, even if extracting the precise information was possible, it may be very costly; it may therefore be

Allowing the signal to be imperfect as assumed in this paper has three salient implications. First, the monitoring probability becomes a decision variable. Second, the contract dictates endogenous limited sanctions and rewards. Third, sanctions are applied in equilibrium. These results are realistic for many applications of monitoring, including that of unemployment insurance benefits. Specifically, maximal sanctions are usually not practiced and monitoring is not applied with certainty.

Since the ability of the planner to acquire costly noisy information is common to many principal-agent settings, I first review models of monitoring in various contexts, with either perfect or imperfect signals.

Aiyagari and Alvarez (1995) allow perfect-signal monitoring in a principal-agent problem with hidden information. In their model, the planner may deprive the agent of her leisure and determine her consumption. The authors characterize the optimal monitoring frequency over compact consumption sets *to avoid making the monitoring technology so powerful that the problem becomes uninteresting.* The existence of consumption bounds lead to non monotone monitoring frequency.

Popov (2009) models verification of hidden information as reported by a worker. Popov keeps the problem nontrivial by assuming that the utility function is bounded from below and that the continuation utility is bounded. With this assumption, the contract delivers bounded sanctions and rewards, depending on the verification result. He finds that monitoring never occurs with certainty and that for a certain class of utility functions, the principal uses verification regardless of this cost.

Newman (2007) studies entrepreneurial risk and occupational self-selection. He uses a static principal-agent problem to study the optimal match between exogenous monitoring technologies and workers who differ by their outside option. The available monitoring technologies differ by their efficiency in a way that can also be interpreted as providing an

more effective for the planner to extract imperfect information on the job-search effort for a lower cost.

imperfect signal. Newman shows that when workers have logarithmic utility, the optimal contract leads to positive assortative matching between workers with a higher level of promised utility and tasks that produce more observable output.

I now turn to review studies that model monitoring specifically in the context of unemployment insurance. Boone, Fredriksson, Holmlund, and van Ours (2007) analyze the design of optimal unemployment insurance in a search equilibrium framework. They allow the signal to be imperfect but they restrict the set of policies among which the optimal policy is chosen. First, the planner does not condition benefits on the worker's history; second, the planner can apply only a fixed decrease in benefits for the remains of the unemployment spell. Their model, however, has the advantage of general equilibrium which my model lacks.

Pavoni and Violante (2007) consider monitoring as part of an optimal Welfare-to-Work program. In their model, the planner can perfectly observe the worker's job-search effort by paying some cost. As a result, the planner monitors this effort with certainty and sanctions or rewards are never needed. For a more complete review on models of job-search monitoring see Fredriksson and Holmlund (2006).

I conclude this section with some empirical evidence on the effect of job-search monitoring and sanctions on labor market outcomes. The effect of job-search monitoring on unemployment duration is usually significant and positive.[4] Johnson and Klepinger (1994) use the Washington Alternative Work-Search Experiment, which includes random assignment of unemployed workers to treatment groups that differ in their job-search requirements. They find that waiving the weekly requirement to record three contacts increases the average unemployment spell by 3.3 weeks. Klepinger, johnson, Joesch, and Benus (1997) evaluate the Maryland Unemployment Insurance Work Search Demonstra-

[4] Van den Berg et al. (2006) consider a model where the efficiency of search is undermined because unemployed workers substitute formal for informal channels. For adverse effects of job search assistance see Van den Berg (1994) and Fougere et al. (2009).

tion. They find that increasing the number of required contacts from two to four decreases the average unemployment spell by 5.9%. They also find that informing the unemployed workers that the contacts will be verified decreases the average unemployment spell by 7.5%.

The evidence on the effects of sanctions is limited yet encouraging. In two empirical studies conducted in the Netherlands, van den Berg, van der Klaauw, and van Ours (2004) and Abbring, van den Berg, and van Ours (2005) find that the unemployment exit rate doubles following a sanction. Lalive, van Ours, and Zweimeller (2005) use Swiss data on benefit sanctions and find that warning about not complying with eligibility requirements and enforcement both have a positive effect on the unemployment exit rate. In addition, increasing the monitoring intensity reduces the unemployment duration of non-sanctioned workers.

3 The model

3.1 The economy

Preferences: Workers have a period utility $u(c) - a$, where c is consumption, a is disutility from job-search effort or work, and u is strictly increasing and strictly concave. Workers discount the future at the discount factor β.

Employment and Unemployment: The worker is either employed or unemployed. During employment, which is assumed to be an absorbing state, the worker exerts a constant effort level e_w and receives a fixed periodic wage w.[5]

During unemployment, the worker searches for a job with an effort level $a \in \{e_l, e_h\}$

[5] The assumption that employment is an absorbing state is widely used in the literature (e.g., Hopenhayn and Nicolini 1997, Pavoni 2009, and Pavoni and Violante 2007). This assumption allows us to analyze one unemployment spell at a time, and does not affect the qualitative characteristics of the optimal policy. Hopenhayn and Nicolini (2009) characterize the optimal unemployment insurance contract in environments in which workers experience multiple unemployment spells.

that is either low or high. This effort is the worker's private information. The job-finding probability, denoted by π_j increases with the job-search effort level $j \in \{l, h\}$. The low job-search effort is interpreted as not actively looking for a job; I therefore set $e_l = 0$ and $\pi_l = 0$. For brevity of notation, I henceforth denote e_h as e, and π_h as π.

Monitoring technology: The monitoring probability $\mu \in [0, 1]$ is a decision variable for the planner. When the worker is monitored, the planner receives a signal on the worker's job-search effort that is either good or bad, denoted by $\{g, b\}$ respectively. The probability of a *good* signal given job-search effort $j \in \{l, h\}$ is θ_j. The signal is only informative if $\theta_h \neq \theta_l$. Hence, I assume, without loss of generality, that $\theta_h > \theta_l$. This means that following a high as opposed to a low job-search effort, a monitored worker is more likely to receive the good signal. Note that this technology does not restrict the value of θ_h to be higher than 0.5. Indeed, there may be some strict monitoring tests generating a useful signal for which θ_h can be very small.

Allowing θ_h to be *smaller than 1* indicates that the planner receives imperfect information regarding the worker's effort. This *false negative* option is a realistic feature of the unemployment insurance system, representing a verification that unjustifiably fails. Allowing θ_l to be *greater than 0* is another source of imperfection, representing a *false positive* result. This imperfection occurs, for example, due to an administrative failure or to caseworker over-generosity.

The cost of monitoring is quasi-concave in the monitoring frequency and equal to $\kappa\mu^\alpha$ per period, with $\alpha \leq 1$. This cost structure, covering constant and increasing returns to scale, discourages the planner from setting the monitoring frequency to 1 under all circumstances.[6]

Decreasing returns to scale seem unreasonable since the monitoring application can be split between caseworkers. Nevertheless, I study convex costs and show that qualitatively,

[6] Given that the administrative institutions for unemployed workers already exist, I assume that monitoring involves no additional fixed cost.

the characteristics of the contract are identical to those of the quasi concave cost.

The assumption that only one monitoring technology is available to the planner can be relaxed by allowing the planner to choose a monitoring technology m from the set $\mathcal{M} = \left\{\kappa^i, \theta^i_h, \theta^i_l, \alpha^i\right\}_{i=1}^N$, which includes N monitoring technologies.

Information structure: Both the worker and the planner observe the employment state, the monitoring signal and the on-the-job effort level.[7] The worker's job-search effort level is private information. This leads to the moral hazard problem.

Timing: Figure 1 shows the model's time frame and the four possible outcomes at the period's end. At the beginning of each period, the planner delivers consumption c to the worker. Then, the worker looks for a job with an effort level e_j and finds a job with probability π_j. If the worker becomes employed, the planner does not apply monitoring.[8] If, however, the worker remains unemployed, she is monitored with probability μ. When monitoring takes place, the planner pays the cost κ and receives the signal $s \in \{g, b\}$.

Figure 1 Approximately Here

Given the realization of the employment state, monitoring, and the signal, the four possible outcomes at the end of the period are: employment (e), unmonitored unemployment (n), monitored unemployment with a good signal (g), and monitored unemployment with a bad signal (b).

3.2 The planner's problem

In general, the optimal contract between the planner and the worker requires conditioning the benefits and the wage tax on the worker's entire history. Spear and Srivastava

[7] This assumption is standard in the optimal unemployment insurance literature, and returns to Hopenhayn and Nicolini (1997). Wang and Williamson (2002) consider the case where the worker's effort level affects the probability of transitions both from unemployment to employment and vice versa.

[8] When a worker becomes employed, the effort level is perfectly revealed to the planner; hence monitoring such a worker is never optimal.

(1987), Thomas and Worral (1988), Abreu, Pearce, and Stacchetti (1990), and Phelan and Townsend (1991) find that all the relevant information for the recursive contract is contained in a one-dimensional object. In the monitoring recursive contract, as in the unemployment insurance contract, this one-dimensional state is the expected discounted utility U promised to the worker at the beginning of each period. This value is updated at the end of each period, according to the outcomes. Hence, this state is governed by all the relevant information in the worker's history. Although this state is not a primitive of the model, using it makes the problem tractable. Once the model is solved, the state is used to recover the allocation for each type of worker.

In what follows, I present the planner problems for an employed worker and an unemployed one.

3.2.1 The planner's problem for an employed worker

Let $W(U)$ be the planner's value from an employed worker who has promised utility U. The planner's problem for an employed worker is:

$$\begin{aligned} W(U) &= \max_{c,U^e} -c + w + \beta W(U^e) \quad (1)\\ s.t. &: \\ U &= u(c) - e_w + \beta U^e, \end{aligned}$$

where U^e is the future promised utility contingent on employment. If $c > w$, then the planner delivers the difference to the worker as a wage subsidy; if $c < w$, then the planner extracts the difference as a wage tax. The constraint in the problem, commonly known as the promise-keeping constraint, states that the expected discounted utility has to be at least equal the utility that was promised to the worker at the beginning of the period.

Given the absence of moral hazard during employment, the solution to the employment problem is full insurance and constant benefits. This implies a constant wage tax or subsidy.

3.2.2 The planner's problem for an unemployed worker

I assume that the government announces its policy at time zero and commits itself to it. This assumption eliminates policies in which the planner deviates from the announced policy (e.g. no monitoring ex-post) whereas workers update their beliefs according to the observed government policy.[9] Given the commitment assumption, the question of whether the planner should monitor or not needs only be examined ex-ante: If the addition of monitoring improves the effectiveness of the contract, then the government should use monitoring and follow the monitoring scheme.

For an unemployed worker, the planner has six decision variables: consumption c, monitoring probability μ, and four continuation values, one for each possible outcome: employment U^e, unmonitored unemployment U^n, monitored unemployment with a good signal U^g, and monitored unemployment with a bad signal U^b.

In addition to these six decisions, the planner recommends a job-search effort level.[10] When recommending a high job-search effort level, the planner needs to support this recommendation by making it worthwhile for the worker to follow it. This is achieved with the *incentive-compatibility* constraint that guarantees that the expected utility for a worker who exerts high job-search effort is at least as high as that for a worker who exerts low job-search effort.[11]

[9] The commitment assumption is typical in the unemployment insurance literature, e.g., Pavoni (2007) and Hopenhayn and Nicolini (1997). There, too, the planner never deviates from the declared scheme.

[10] If the planner recommends the low effort level, then there is no need to set incentives. The solution is constant benefits and a constant wage tax. This solution can be achieved because while $\pi > 0$, the probability of finding a job associated with zero effort is zero. The planner therefore knows that a worker who received a job-offer must have expended high effort when searching for that job. The planner can use this observation to apply punishments severe enough to discourage workers from not following the low job-search effort recommendation.

[11] For sufficiently high enough levels of promised utility, creating incentives by spreading future promised utilities is too costly; hence, the planner recommends low job-search effort and implements full insurance (Pavoni and Violante (2007) refer to this state as Social Assistance). To fully characterize the optimal monitoring policy, I describe the monitoring policy while assuming that it is always desirable to create

Let $V(U)$ be the planner's value from an unemployed worker who has promised utility U. The planner's problem for an unemployed worker is:

$$
\begin{aligned}
V(U) &= \max_{c,U^e,U^n,U^g,U^b,\mu} -c+\beta\{\pi W(U^e)+(1-\pi)(1-\mu)V(U^n) \\
&\qquad +\mu\left[\theta_h V(U^g)+(1-\theta_h)V(U^b)\right]-\kappa\mu^\alpha\}\} \\
s.t. &: \\
U &= u(c)-e+\beta\pi U^e+\beta(1-\pi)\left[(1-\mu)U^n+\mu\left(\theta_h U^g+(1-\theta_h)U^b\right)\right] \\
U &\geq u(c)+\beta\left[(1-\mu)U^n+\mu\left(\theta_l U^g+(1-\theta_l)U^b\right)\right], \qquad (2)
\end{aligned}
$$

where the objective function includes the cost of consumption payments to the worker and the discounted weighted values of the four possible outcomes. The constraints are *promise keeping* and *incentive compatibility*, discussed above. Since the incentive-compatibility constraint is binding at the optimum, I will henceforth use the equality sign in this constraint.[12]

By applying fairly standard results in dynamic programming, one obtains that $W(U)$ and $V(U)$ are continuous functions, that are decreasing, concave and continuously differentiable in U.[13]

incentives to expend high job-search effort. According to the calibration, social assistance is optimal only for those values of promised utility associated with extremely high consumption levels, around 10 times the wage. Thus, in the simulations conducted the workers' promised utility values at the balanced budget point are far below these values.

[12]This is the case because delivering an expected discounted utility that is higher than the required one, costs more.

[13]Since the monitoring cost is concave in μ, $V(U)$ can be improved by using lotteries over the monitoring probability. This is a linear programming problem that can be solved numerically, as Phelan and Townsend (1991) show. I abstract from such lotteries in this section. In the quantitative analysis I use a linear monitoring cost that makes the use of such lotteries redundant.

4 Calibration

In order to characterize the optimal contract and to assess the savings associated with monitoring I calibrate the model to the US economy.

Table 1 lists the model's parameters. The unit of time is set to one month. Preferences are log utility in consumption. The monthly discount factor β is set to 0.9959 to match an annual interest rate of 5% (Cooley, 1995). Monthly earnings, w, are set to \$2,800, which is the median monthly earnings of all workers (DOL, 2006a). The job-finding probability π is set to 0.17, based on the CPS-derived data constructed by Shimer (2005). The disutility of work effort, e_w, which equals the disutility of job-search effort, e, is equal to 0.67 as in Pavoni and Violante (2007).

The monitoring technology is characterized by four parameters: the probabilities of a good signal given high and low job-search effort, θ_h and θ_l, respectively, the monitoring cost per unit of monitoring κ, and the curvature of the monitoring cost α.

The calibration of a good signal given the high and low job-search effort levels (θ_h, θ_l) of the current US system is quite challenging for two reasons. First, while in the model all workers have the incentives to search for a job with high effort, it is unclear as to what fraction of workers indeed have those incentives. I therefore denote by ξ, the fraction of workers who search for a job with a high effort in the current system. Second, θ_h and θ_l stem from a system imperfection that is unobservable to either the case worker or the economist.

Fortunately, the US Department of Labor is engaged in a systematic and detailed analysis of the adequacy of payments in the current UI system (Woodbury (2002), DOL (2006b), Vroman and Woodbury (2001)). These studies reveal the fraction of overpayment and underpayment (denial errors) paid to workers specifically for non-separation errors, thus excluding reasons such as ineligibility due to insufficient previous earnings and quitting.

I proceed by providing explicit equations that connect θ_h and θ_l to the observed data, taking into account that only a fraction of workers, ξ, exerts the high effort level. First, the fraction of *overpayment*, denoted by z_1, is equal to those who did not exert high effort yet received payments relative to all those who received payments: $\frac{(1-\xi)\theta_l}{(1-\xi)\theta_l+\xi\theta_h}$. Similarly, the fraction of *underpayment*, denoted by z_2, is equal to: $\frac{\xi(1-\theta_h)}{(1-\xi)\theta_l+\xi\theta_h}$. Finally, the fraction of monitored workers who were sanctioned, denoted by z_3, is equal to: $\xi * (1-\theta_h) + (1-\xi) * (1-\theta_l)$.

Those three equations can be rewritten as an explicit unique solution of $\{z_1, z_2, z_3\}$:

$$\begin{aligned} \theta_h &= \frac{1-z_1}{z_2+1-z_1} \\ \theta_l &= \frac{z_1 * (1-z_3)}{z_3 + (1-z_3)(z_1-z_2)} \\ \xi &= (1-z_3)\left[z_2+1-z_1\right]. \end{aligned} \tag{3}$$

Based on various sources, the values for $\{z_1, z_2, z_3\}$ are $\{1.4\%, 1.9\%, 16\%\}$, respectively.[14] The implied values for the monitoring technology are: $\theta_h = 0.98$, $\theta_l = 0.08$ and $\xi = 0.84$.[15]

The calibration of the signal probabilities implies a rather precise monitoring technology. The high value of θ_h is influenced by actions taken after the sanctions were imposed, such as appeals, and redetermination (see Table ES-1 in DOL (1999) and DOL (2006b)).

The low level of θ_l can be affected by measures taken by workers to manipulate the system. If this is the case, then the value of overpayment (z_1) is higher and the value of θ_l above is underestimated. The sensitivity analysis that follows shows, however, that the results are robust even to large increases of that value.

[14] The basis for z_1 and z_2 is Table 1 in Woodbury (2002), which gives the percentage of overpayment as 7.2% and of underpayment as 3.4%. The fraction of overpayment due to non-separation errors is 19.8% (DOL (2006b)) and for wrongful denials it is 57% (Vroman and Woodbury (2001)). z_3 is equal to the monthly probability of sanctions (ϕ) of 3.3% (Grubb, 2000), over the monthly monitoring frequency, μ^{ACT}, of 0.20 (see Appendix C).

[15] The high proportion of workers who exert a high effort (0.84) is consistent with the observation of Pavoni and Violante (2007) that the current system in the US provides excessive incentives.

Before moving to the calibration of the remaining monitoring parameters, it should be stressed that the analysis presented in this paper is based on the actual monitoring technology applied in the US. Another direction of analysis is optimal monitoring precision, given a monitoring cost that increases with precision as in Boone, Fredriksson, Holmlund, and van Ours (2007). Such a cost-effectiveness analysis may lead to using either a lower precision-lower cost monitoring technology, or a higher precision-higher cost one.

The monitoring cost κ is based on data from The Minnesota Family Investment Program (MFIP, 2000), where each caseworker was responsible for 100 clients and, among other tasks, was assigned to apply sanctions, assist with housing, and document client activities. Based on monthly gross earnings of \$3,000 per caseworker and the described case load, the value of κ is \$30 per month per each unemployed worker monitored.[16] This value is an approximation because, on one hand, the caseworkers were also engaged in activities other than monitoring and, on the other, they may have not monitored every month. Interestingly, although Boone, Fredriksson, Holmlund, and van Ours (2007) use completely different data sources, their equivalent value of $\kappa = \$27$ is surprisingly close to the calibration presented here.

Since the verification of employment contacts does not imply clear increasing or decreasing returns to scale I assume that $\alpha = 1$. I study the effect of other values of α in the sensitivity analysis.

Table 1 Approximately Here

5 Results

This section is comprised of two parts. In the first, I discuss the characteristics of the optimal monitoring policy. In the second, I estimate the value of monitoring by comparing

[16] Median annual earnings for *Community and Social Services Occupations* in the US was \$36,390 in 2006 (Department of Labor, 2006).

the current model to a model without a monitoring technology (See Appendix B for the solution method).

5.1 Optimal monitoring policy

The optimal contract is described recursively by six functions of the state variable U : $\left\{c, U^e, U^n, U^g, U^b, \mu\right\}$. I begin with the mapping of current promised utility to next period's promised utility. In the optimal contract, the four future values, corresponding to the four possible outcomes, endogenously create implicit rewards and sanctions.

Figure 2 shows the mapping of promised utility by outcome across periods. The horizontal axis is promised utility at the beginning of the period. The vertical axis is the next period's promised utility. The four future promised utilities are ordered as follows: U^e, U^g, U^n, U^b. This follows directly from the likelihood ratios, with $l^e > l^g > l^n > l^b$, where: $l^e = 1, l^g = \frac{(1-\pi)\theta_h - \theta_l}{(1-\pi)\theta_h}, l^n = -\frac{\pi}{1-\pi}, l^b = \frac{(1-\pi)(1-\theta_h)-(1-\theta_l)}{(1-\pi)(1-\theta_h)}$. Thus, the monitoring signal implies endogenous prize and sanction relative to unmonitored unemployment.[17] If a good signal is realized then the worker receives a prize in continuation value of $U^g - U^n > 0$. If a bad signal is realized then the worker endures a sanction of $U^n - U^b > 0$.

Upon employment - an outcome that can only happen in the model if the worker exerts a high job-search effort - promised utility increases; upon monitoring with a good signal, the worker receives a reward that is only slightly below that of employment; upon unmonitored unemployment, the promised utility changes only slightly; finally, upon monitoring with a bad signal the worker experiences a severe decrease in promised utility, implying that the planner finds the bad signal highly informative and helpful in creating the necessary incentives.

The values of U^n, U^g, and U^b, are jointly determined by the following condition, based on the three first-order conditions: $V'(U^n) = \theta_h V'(U^g) + (1-\theta_h) V'\left(U^b\right)$. Up to a linear

[17] The likelihood ratio is defined as follows. For each outcome $i \in \{e, g, b, n\}$ define p_1^i, p_2^i as the probability of the outcome given high and low effort levels, respectively. Then $l^i = \frac{p_1^i - p_2^i}{p_1^i}$.

approximation for the derivative of the planner's value function, the ratio of the sanction over the prize in continuation values $\frac{U^n - U^b}{U^g - U^n}$ is equal to $\frac{\theta_h}{1-\theta_h}$. This condition, together with the calibration of θ_h at a level close to 1, implies that the sanction level is significantly higher than the reward (the calibrated value of the ratio is 49). This result is consistent with the absence of prizes in the actual monitoring scheme, as prizes are relatively small.

More generally, in the optimal contract the prize and the sanction balance each other. For high θ_h signals, monitoring allocates modest prizes with a high probability and severe sanctions with a low probability. For low θ_h signals, monitoring allocates high prizes with a low probability and modest sanctions with a high probability.

Figure 2 Approximately Here

I now move to discuss monitoring frequency and utility spread decisions. Figure 3 shows monitoring frequency by promised utility.[18] Monitoring frequency varies across its complete support: for sufficiently low values of promised utility the cost of monitoring is too high and no monitoring takes place; for sufficiently high values of promised utility the opposite is the case, with monitoring frequency at its maximum value.

As for the spreads, observe that given the calibration of θ_h, U^b is far lower than the other three future utilities. To demonstrate the dynamics of the spreads, I focus on the level of U^b relative to U^n. The dynamics of the remaining spreads are identical.

Define the *relative consumption sanction* as the fraction by which the next period's current consumption decreases upon a bad signal relative to that of unmonitored unemployment. Figure 4 shows the relative consumption sanction by promised utility. Note that the sanction is plotted only for levels of promised utility at which $\mu > 0$.

Figures 3 and 4 Approximately Here

[18] The high span of promised utility in this figure, ranging from equivalent consumption levels of \$20 to \$200,000 per month, is used to demonstrate the contract's qualitative characteristics. As discussed below, the span of promised utility that includes the complete support of μ can be much smaller (Figure 7). The subsequent quantitative results are based on a fine grid over a much smaller span.

Therefore, the optimal contract dictates that as the generosity of the welfare system increases, the planner monitors the unemployed more frequently but imposes more moderate sanctions. This result is consistent with the observation of Boone, Fredriksson, Holmlund, and van Ours (2007) that when comparing US and Sweden's monitoring policies, the number of sanctions is inversely related to the severity of the penalty.

The policy implication of this result is that the generosity of the welfare system implies to what extent the monitoring policy should emphasize the sanction or the monitoring frequency.[19]

In order to understand the driving force behind the response of monitoring frequency and spread in future payments to promised utility it would be valuable to characterize the contract analytically. This would permit sharper statements about which parameters shape the optimal contract.

Such a characterization is very challenging for the infinite-horizon model. I therefore describe a two-period model in Appendix A that captures the same economic forces as the infinite-horizon model. Specifically, the possible outcomes, their probabilities, and the choice variables of the planner are all identical to the infinite-horizon model.

The analytical characteristics of the optimal contract for the two-period model include two propositions regarding the monitoring frequency and the spreads of future payments. These propositions establish that the contract characteristics described above and depicted in figures 3 and 4 are kept for any parametrization of the model. These parameters are those of the worker's preferences $\{\beta, e\}$, the labor market $\{\pi, e\}$, and the monitoring technology $\{\theta_h, \theta_l, \kappa, \alpha\}$.

The key assumption that is required for the main result to hold is log-utility from consumption. To understand the importance of this assumption consider the cost of the

[19] Pavoni, Setty, and Violante (2012) study Welfare-to-Work programs. They show how the generosity of the welfare system affects the nature of the optimal policies assigned to the unemployed worker. While high generosity implies that search-based policies are optimal, low generosity implies work-based policies.

two instruments of monitoring. The cost of applying monitoring is the monitoring cost κ. This cost is independent of the state of the worker. The cost of spreading out future utilities exists because the worker is risk averse and the planner needs to compensate the worker for the uncertainty in payments. I demonstrate below that for log utility this cost increases with promised utility. Hence, as promised utility increases, the planner shifts the composition of the two monitoring components by increasing the monitoring frequency and decreasing the spreads.

Taken together, figures 3 and 4 demonstrate additional features of the optimal contract that are proven in the two-period model. First, the sanction and the spread complement one another; as one increases the other decreases. Second, when the monitoring frequency is constant, the sanction remains constant as well. This occurs for $\mu = 1$ and for low levels of promised utility when the resolution of μ creates steps in the monitoring frequency. These results hold for any parametrization of the model as well.

Running the model with different levels of risk aversion in the CRRA class reveals a clear pattern: the dynamics of the monitoring probability and the spreads flip exactly at the point where the coefficient of relative risk aversion falls below $\frac{1}{2}$. In other words, μ increases in U and the spreads decrease for any $\sigma > \frac{1}{2}$, μ and the spreads are invariant in U if $\sigma = \frac{1}{2}$, and μ decreases in U and the spreads increase for $\sigma < \frac{1}{2}$.

I demonstrate the significance of $\sigma = \frac{1}{2}$ in a simple two-period model with no monitoring and no current compensation. The problem thus becomes:

$$\begin{aligned} V(U) &= \max_{c^e, c^n} \{\pi(w - c^e) - (1-\pi)c^n\} \\ s.t. &: \\ U &= -e + \pi u(c^e) + (1-\pi)u(c^n) \\ U &\geq u(c^n). \end{aligned}$$

The solution to this problem is $c^n = u^{-1}(U)$, $c^e = u^{-1}\left(U + \frac{e}{\pi}\right)$. The first-best solution is constant consumption across both future states, i.e., $c^n = c^e = u^{-1}(U+e)$. The difference between the first-best and the second-best planner's cost of providing consumption is then:

$$\pi u^{-1}\left(U+\frac{e}{\pi}\right)+(1-\pi)u^{-1}(U)-u^{-1}(U+e), \tag{4}$$

which is equal to the cost of spreading out the future values.

Using CRRA utility and differentiating this cost with respect to promised utility gives:

$$\pi\left\{(1-\sigma)\left(U+\frac{e}{\pi}\right)\right\}^{\frac{\sigma}{1-\sigma}}+(1-\pi)\left\{(1-\sigma)U\right\}^{\frac{\sigma}{1-\sigma}}-\left\{(1-\sigma)(U+e)\right\}^{\frac{\sigma}{1-\sigma}}. \tag{5}$$

The cost of spreading out future utilities increases with U if and only if this derivative is positive. This condition holds if and only is $\sigma > \frac{1}{2}$. To see this notice that the first two terms in (5) comprise a lottery, whose expected value $(U+e)$ appears in the third term. The difference between the value of the lottery and the value of the certainty equivalent is positive if and only if $f(x) = \{(1-\sigma)x\}^{\frac{\sigma}{1-\sigma}}$ is a strictly convex function. This holds if and only if $\sigma > \frac{1}{2}$.[20]

This dynamic of the costs of the spreads explains the characterization of the optimal contract as a function of σ. In the model with monitoring the planner chooses the optimal mix of monitoring frequency and spreads for satisfying the incentive-compatibility constraint. As promised utility changes, the cost of spreads changes according to the value of σ. Since the planner's cost of applying monitoring is fixed, she adjusts the combination of monitoring frequency and spreads accordingly.[21]

[20] Newman (2007) finds that $\sigma = 0.5$ is the critical value for determining the distribution of wealth across entrepreneurs and workers.

[21] An interesting implication of this result is that the further the level of risk aversion is away from $\frac{1}{2}$, the sensitivity of μ to promised utility is greater because the change in the cost of spreading consumption is greater.

5.2 The value of monitoring

The planner's value from the optimal monitoring policy lies between the value of optimal unemployment insurance, which is a special case of monitoring with $\mu = 0$, and the value of the first best. Thus, to study the effectiveness of monitoring relative to unemployment insurance, I define $\nu = \frac{V^{MON} - V^{OUI}}{V^{FB} - V^{OUI}}$, where V^{MON}, V^{OUI} and V^{FB} are the planner's values for optimal unemployment insurance with monitoring, optimal unemployment insurance, and the first best, respectively.[22] The difference $V^{FB} - V^{OUI}$ can be considered as the moral hazard cost if no monitoring was available. The metric ν is, therefore, the percentage of the moral hazard cost saved by including monitoring.

Figure 5 shows the value of monitoring over the support of promised utility. Monitoring is relatively more effective at high levels of promised utility because for log-utility preferences the cost of spreads increases with promised utility. At sufficiently low levels of promised utility, the optimal monitoring policy coincides with the optimal unemployment insurance policy. At the other extreme of promised utility, savings strictly increase even though μ is constant. This occurs because the cost of spreads continue to increase.

Figure 5 Approximately Here

Since the effectiveness of monitoring varies significantly across states, it would be interesting to measure the savings at the level of promised utility that balances the government's budget. The balanced budget point is U_0^*, such that $V(U_0^*) = 0$. This is the level of promised utility for when the costs of benefits, wage subsidies and monitoring are exactly covered by the tax revenues.[23] At U_0^* for the model with no monitoring, the addition of monitoring saves 82% of the moral hazard cost.

[22] The model with no monitoring is closely related to the model used in Hopenhayn and Nicolini (1997). The main difference is that in Hopenhayn and Nicolini the job-search effort level is continuous and not discrete. For the sake of consistency I use a discrete level of effort in both models.

[23] This point is unique because $V(U)$ is strictly monotone in U.

At U_0^* the monitoring frequency is 6% and the relative consumption sanction, which is approximately a permanent decrease in consumption, is 4.8%. The other three states lead to deviations on a scale much smaller than that of the relative consumption sanction.

In absolute values the savings at the balanced budget point amounts to $87 per worker - out of the $106 possible. The potential savings of $106 is limited since the optimal unemployment insurance contract a la Hopenhayn and Nicolini (1997) already closely approaches the first best by being conditional on the complete history of the worker and allowing the tax to depend on that history as well.

5.2.1 Who should be monitored?

As noted above, monitoring is especially effective for workers for whom the cost of spreading utilities is high. I have so far discussed the effects of promised utility and risk aversion on this cost. There are, however, other parameters that affect the cost of spreading utilities.

The cost of spreading future utilities increases with e. As e increases, the planner needs to provide stronger incentives for the worker to exert the high effort. In the extreme case of $e = 0$, there is no need to spread out future values at all. In the other extreme case of very high disutility from search, the cost would be too high to rationalize the high-effort recommendation.

In addition, the cost of spreading future utilities decreases with π. As π increases the job-finding probability associated with a high effort is further separated from the low effort one. This means that the information that the planner receives from the employment state of the worker becomes more precise. The extreme case of $\pi = 1$ is isomorphic to observable effort. In the other extreme case for $\pi = 0$ the planner cannot provide incentives for the worker to expend a high effort.[24]

[24] The effects of $\{e, \pi\}$ can also be seen analytically in (4) by differentiating the cost of spreading utilities with respect to either e or π.

Monitoring will thus be relatively more effective not only for more-generous welfare systems but also for two types of workers: discouraged unemployed workers who have a high disutility from work (or a high utility from leisure) and workers with low job-finding probability. This finding well fits the application of monitoring to such workers.

Quantitatively, changes in disutility from work or the job-finding probability can substantially affect the contract. In the case of log utility, for example, changes in e or in π affect the cost of spreads exponentially. Note that unlike the effect of promised utility on spreading costs that is sensitive to risk aversion, the effects of e and π on the cost of spreads are independent of risk aversion.

But what about the dynamics of monitoring over the unemployment spell? Conditional on unemployment, promised utility decreases along the unemployment spell; hence, qualitatively monitoring should decrease and sanctions should increase (for $\sigma > \frac{1}{2}$). Quantitatively, however, for log utility the optimal monitoring scheme is fairly insensitive to such changes in promised utility. The planner can therefore use a fixed monitoring frequency together with a fixed sanction. This relatively simple monitoring scheme would deliver almost the same gains as the optimal one.

5.2.2 What makes monitoring effective?

In optimal unemployment insurance, the planner is required to spread out future utilities to create the job-search incentives. This action is costly since the worker is risk-averse. Thus, the reduction in the planner's cost due to monitoring can only be achieved by consumption smoothing. To demonstrate this as well as assess the smoothing intensity, I simulate the consumption paths for the optimal unemployment insurance model and for the monitoring model.

Figure 6 shows three examples of consumption paths according to the two policies. In each example, the worker starts off unemployed with a promised utility level of U_0^*, stays unemployed for 3 periods, and then finds a job. In the top panel, there is no monitoring. In the middle panel, monitoring is applied in periods 1, 2 and 3, resulting in a good signal in all three cases. In the bottom panel, monitoring is applied once in period 1, resulting in a bad signal.

Figure 6 Approximately Here

In the absence of additional signals, the consumption paths for optimal unemployment insurance for these three cases are identical and are presented here as a reference. Consumption in the unemployment insurance model first decreases monotonically and then increases significantly when the worker finds a job. These shifts in consumption are required for creating the necessary incentives for unemployed workers to expend high effort given that only two possible outcomes are possible.

In contrast, consumption in the monitoring model varies very little, excluding the third panel, where the worker is sanctioned. Note, however, that sanctions are a rare event; they only happen when both monitoring and a bad signal occur. At the balanced budget point the unconditional probability of a sanction, $\mu * (1 - \theta_h)$, is about 0.12%. This is equivalent, on average, to sanctioning one of about 800 unemployed workers or sanctioning an unemployed worker once every 70 years!

The simulation shows that due to the additional information regarding the job-search effort, monitoring allows the planner to smooth unemployed workers' consumption. Simulating the model over 60 periods and 5,000 workers shows that the standard deviation of consumption in the monitoring model is less than half the standard deviation of consumption in the model without monitoring.

5.2.3 Sensitivity Analysis

The comparison above between the models with and without monitoring relies on the effectiveness of monitoring, which in turn relies on the four parameters of monitoring technology: the probabilities of a good signal given high and low job-search effort θ_h and θ_l, respectively; the cost per unit of monitoring κ; and the concavity of the monitoring cost α. In order to examine the sensitivity of the savings to these parameters I analyze the response of savings at the balanced budget point to various values of these four parameters.

The probability of a good signal given the high job-search effort θ_h determines the precision of the information extracted by applying monitoring. As θ_h increases, the planner receives more accurate information on the level of the worker's job-search. In the extreme case when $\theta_h = 1$, it is possible to get arbitrarily close to the first-best allocation by using a combination of a very low monitoring frequency (that costs very little) with an extremely severe punishment that is never applied.

Table 2 presents the savings at the balanced budget point for various levels of θ_h. Holding θ_l and κ fixed, as θ_h increases beyond the benchmark value, the efficiency of monitoring increases as expected. As θ_h decreases, the savings level decreases sharply; at a value of $\theta_h = 0.90$ the savings is 61%. Note, however, that the system of equations (3) implies that the lower bound for θ_h is 0.84 (since $z_3 = 0.16$ and $\theta_h > \theta_l$).

Table 2 Approximately Here

The sensitivity analysis of θ_l in Table 3 shows that monitoring's efficiency depends on the difference between the precision of the two signals (θ_h, θ_l). As θ_l gets closer to θ_h, savings decrease significantly. As noted above, if overpayment is underestimated because workers can manipulate the system then the value of θ_l is underestimated. Note however, that according to (3) when z_1 increases, in addition to the increase in θ_l, the fraction of workers with high job-search effort (ξ) decreases significantly while θ_h does not change much. For example, if $z_1 = 0.7$ then $\theta_h = 0.94, \theta_l = 0.8$ and $\xi = 0.27$. In this case the value of ξ is inconsistent with the observation of Pavoni and Violante (2007) mentioned above.

Table 3 Approximately Here

Table 4 shows the savings for various values of the monitoring cost κ. First, note that when $\kappa = 0$, the first best is not achieved because free monitoring provides imperfect information.[25] Second, as the cost of monitoring increases the planner uses monitoring less frequently and the level of savings decreases. Nevertheless, even when $\kappa = 100$ - a monitoring cost that is higher by more than three times than the benchmark calibration - savings stands at about 70%.

Table 4 Approximately Here

Table 5 shows the savings for various values of the cost curvature α. Since κ is kept fixed, increasing the curvature parameter α implies lower costs and increased savings. More interesting is the dynamics of the monitoring frequency and the spreads over U given convex costs. While V is concave in μ for any quasi-concave cost, it is also concave for some convex costs (see proof of Claim 1 in Appendix D). Since supermodularity (see proposition 1 in Appendix 1) holds for any cost curvature, the dynamics of the monitoring probability and the spreads are expected to hold, at least weakly, for convex costs as well.

Table 5 Approximately Here

Figure 7 shows the monitoring frequency for $\alpha \in \{0.5, 1.0, 1, 5\}$. Figure 8 complements figure 7 by showing the relative consumption sanction for the same three cases. The two extreme cases show that while the characteristics of the contract are qualitatively the same, the sensitivity to changes in promised utility depends on the cost curvature. This demonstrates the wide spectrum of results that the model can generate. For some parameterizations, such as high α, choosing $\mu \in \{0, 1\}$ and the corresponding sanction may be a decent rule of thumb. For other parameterizations, such as a low α, a fixed monitoring frequency and a fixed sanction may be close to optimal.

[25] When $\kappa = 0$, the planner monitors with probability 1.0. However, since the signal is imperfect, the planner cannot know with certainty what the job-search effort level was. Therefore, the planner still needs to condition the promised utility on outcomes that will materialize in equilibrium, which is costly.

Figures 7 and 8 Approximately Here

Note that the monitoring frequency for any two levels of curvature α_1 and α_2 cross when the marginal cost of monitoring is equalized at $\mu = \exp\left(\frac{\log(\alpha_1/\alpha_2)}{\alpha_2 - \alpha_1}\right)$.

6 Concluding remarks

Governments monitor the job-search activities of unemployed workers in order to increase the effectiveness of unemployment insurance. Doing so involves randomly monitoring job-search effort and receiving, at a cost, a signal that is related to the effort level. Such additional information plays an important role in the design of unemployment insurance schemes.

In this paper I added a monitoring technology to the optimal unemployment insurance framework. The framework allowed characterization of the optimal contract and evaluation of the gain from using the monitoring technology.

Allowing the signal to be realistically imperfect had two important advantages. Qualitatively, the optimal-contract included a non-trivial decision of the monitoring probability; it dictated endogenous limited sanctions and rewards; and sanctions were applied in equilibrium. Quantitatively, this technology permitted a reasonable estimation of the effectiveness of monitoring based on the actual monitoring technology in the US.

I showed how the two components of monitoring, the monitoring frequency and the spread of continuation values, complement each other, depending on the state of the worker and utility from consumption. For CRRA utility, the monitoring frequency increased and the spreads decreased with promised utility if and only if $\sigma > \frac{1}{2}$. The driving force behind the result was the realization that the cost of spreading out future utilities increases with the continuation value if and only if $\sigma > \frac{1}{2}$, while the cost of monitoring is invariant to that value.

In the quantitative analysis conducted at the balanced budget point, I showed that compared to optimal unemployment insurance, monitoring saves about 80% of the cost associated with moral hazard. The gain was achieved by a decrease of more than half in the standard deviation of consumption.

One limitation of the framework used in this paper is that the model's tractability depends on the assumption that the planner controls the worker's consumption, i.e., no savings is allowed on the worker's side. As pointed out by Abdulkadiroglu, Kuruscu, and Şahin (2002) and Shimer and Werning (2008), allowing workers to accumulate unobservable savings may significantly affect the results. Nevertheless, the recursive contract framework demonstrates the main trade-offs when a costly imperfect signal is available. It appears that as long as differentiation of future payments is necessary, not only will monitoring be effective, but the trade-offs presented in this framework should likewise hold. Also to be considered is that when the framework presented here is applied to other contexts, such as crime and punishment, the no-savings assumption is perfectly reasonable.

Another limitation of that framework is that the sanctions are unjustified. This occurs because the incentive-compatibility constraint in the model holds. Nevertheless, these sanctions need to be placed in the contract to keep the workers' incentives in place. Note that the same concept of unjustified punishments holds in optimal unemployment insurance. There, conditional on unemployment, the worker experiences benefit cuts even though the planner is aware that the worker abides the effort recommendation. A more realistic model would include unobserved heterogeneity in disutility from job-search and from work. Under such circumstances, the sanctions in equilibrium would be partially justified.

Alternatively, heterogeneity can be introduced through wages. This would allow conditioning the initial level of promised utility on the wage of each type of worker, thus indexing the unemployment insurance benefits to the worker's wage. Indeed, this practice is applied in most OECD countries.[26]

According to Grubb (2000), there are significant differences across countries in all the policy's main characteristics. For example, consider Australia and the US. In Australia, a moderate sanction of 18% of the benefits level is applied for a duration of 26 weeks. This is considerably a longer and a more spread out sanction relative to the one week denial of benefits in the US. At the same time, Australia's annual sanction rate, standing at 1.2%, is relatively low when compared with the 33% in the US. An extended model could reveal whether the variation in policies follows labor market characteristics or some inefficiencies.

Although the paper's focus was the monitoring of unemployed workers, the modeling environment presented was rather general. This implies that the model can be used for a wide array of problems, when the planner is able to use a costly imperfect signal to learn about the agent's hidden information or action.

The analysis of monitoring can also be applied to systems in which the probability of a good signal in the wake of high effort is very low. In that case, the prize relative to the sanction will be very high. Then, a near optimal implementation of the contract may include a prize only. Indeed, this characterization is consistent with competitions.

[26]This heterogeneity in wages would reduce and possibly eliminate the result that for high levels of promised utilities the planner recommends a low job-search effort: once high levels of promised utilities will be associated with high wages, the gain from employment to the planner may dominate the cost of setting the incentives for the high job-search effort.

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APPENDIX A: A TWO-PERIOD MODEL

In the absence of theoretical results for the infinite-horizon model, this appendix includes a theoretical characterization of a two-period model that captures the same economic forces as the infinite-horizon model. Specifically, the possible outcomes, their probabilities, and the choice variables of the planner are all identical to the infinite-horizon problem. The following adjustments take place in the two-period model: $W(U)$ becomes $w - c^e$; U^i becomes $u(c^i)$ for $i \in \{e, n, g, b\}$; and $V(U^i)$ becomes $-c^i$ for $i \in \{n, g, b\}$.

I impose a logarithmic utility function. The generalization of the results to CRRA preferences is discussed in Section 5. Finally, for simplicity, I assume that $\beta = 1$.

The problem of the planner for an unemployed worker is then:

$$\begin{aligned} V(U) &= \max_{c, c^e, c^n, c^g, c^b, \mu} -c - \pi(c^e - w) - (1-\pi)\{(1-\mu)c^n + \mu\left[\theta_h c^g + (1-\theta_h)c^b\right] - \kappa\mu^\alpha\} \\ & \quad s.t. \\ U &= u(c) - e + \pi u(c^e) + (1-\pi)\left[(1-\mu)u(c^n) + \mu\left(\theta_h u(c^g) + (1-\theta_h)u\left(c^b\right)\right)\right] \\ U &\geq u(c) + \left[(1-\mu)u(c^n) + \mu\left(\theta_l u(c^g) + (1-\theta_l)u\left(c^b\right)\right)\right] \end{aligned} \tag{6}$$

For the exposition of the proof it is useful to set the problem in two steps. In the first step we solve for $M(U, \mu)$, which is identical to (6) above **except that the monitoring frequency is given exogenously**. In the second step we solve for $V(U) = \max_\mu M(U, \mu)$. The Lagrangian of $M(U, \mu)$ is:

$$\begin{aligned} & -c - \pi(c^e - w) - (1-\pi)\left\{(1-\mu)c^n + \mu\left[\theta_h c^g + (1-\theta_h)c^b\right] - \kappa\mu^\alpha\right\} \qquad (7) \\ & +\lambda_1\left\{U - u(c) + e - \pi u(c^e) - (1-\pi)\left[(1-\mu)u(c^n) + \mu\left(\theta_h u(c^g) + (1-\theta_h)u\left(c^b\right)\right)\right]\right\} \\ & +\lambda_2\left\{U - u(c) - (1-\mu)u(c^n) - \mu\left(\theta_l u(c^g) + (1-\theta_l)u\left(c^b\right)\right)\right\}, \end{aligned}$$

where λ_1 and λ_2 are the Lagrange multipliers of the promise keeping and incentive-compatibility constraints, respectively. Note that both λ_1 and λ_2 are negative.

I start the characterization of the optimal contract with two results regarding the relative values of consumption levels. The first result refers to the ranking of the future consumption levels.

Lemma 1 *In the optimal solution,* $c^e > c^g > c^n > c^b$.

Proof. This follows directly from the likelihood ratios with $l^e > l^g > l^n > l^b$, where: $l^e = 1, l^g = \frac{(1-\pi)\theta_h - \theta_l}{(1-\pi)\theta_h}, l^n = -\frac{\pi}{1-\pi}, l^b = \frac{(1-\pi)(1-\theta_h)-(1-\theta_l)}{(1-\pi)(1-\theta_h)}$. ■

According to Lemma 1 the monitoring signal creates, relative to unmonitored unemployment, an endogenous prize $c^g - c^n > 0$ when the good signal is realized, and an endogenous sanction $c^n - c^b > 0$ when the bad signal is realized. The next result refers to the relationship between future consumption levels and the shadow prices.

Lemma 2 *In the optimal solution current consumption equals to an average of future consumption levels, weighted by the probabilities given high effort for outcomes* $i \in \{e, n, g, b\}$.

Proof. The first-order conditions of (7) with respect to the choices of future consumption levels $c^i,\ i \in \{e, n, g, b\}$ are:[27]

$$c^i = -\lambda_1 - \lambda_2 l^i \tag{8}$$

Averaging (8) over outcomes i with the respective high-effort probabilities yields that $\lambda_1 = -\pi c^e - (1-\pi)\left\{(1-\mu)\,c^n + \mu\left[\theta_h c^g + (1-\theta_h)\,c^b\right]\right\}$. Using the first-order condition of (7) with respect to the choice of current consumption yields $\lambda_1 = -c$, implying that $\pi c^e + (1-\pi)\left\{(1-\mu)\,c^n + \mu\left[\theta_h c^g + (1-\theta_h)\,c^b\right]\right\} = c = -\lambda_1$. ■

[27] Note that for brevity of notation, I omit the state $\{U, \mu\}$ from $\left\{c^i, \lambda_1, \lambda_2\right\}$ although these are functions of the state.

Lemma 2 simply states that the shadow prices of the promise keeping constraint is equal to the weighted average of the reciprocals of marginal utility, which for log utility equals to consumption itself.

Before moving to the main propositions regarding the optimal contract, we can gain insights on the optimal contract from the two Lemmas above. First, using (8) for c^g, c^n and c^b implies that $c^n = \theta_h c^g + (1 - \theta_h)c^b$. Thus, in the optimal contract the prize and the sanction balance each other. Also observe that as the precision of the monitoring signal increases, the ratio of sanctions to prizes, $\frac{\theta}{1-\theta}$, increases. For high precision signals, monitoring allocates modest prizes with a high probability and severe sanctions with a low probability.

Second, according to the likelihood ratios, as monitoring signals become more precise (θ_h increases, θ_l decreases, or both), c^g and c^b move further away from c relative to the other two levels of consumption c^e and c^n. In the extreme case of a non-informative signal, that is when $\theta_h = \theta_l$, c^g and c^b are equal to c^n. In the other extreme case, when $\theta_h = 1$, the sanction explodes relative to any other spread.

Note that as long as $\theta_h > \theta_l$, $\theta_h = 1$ provides a perfect signal regardless of the value of θ_l. This is so because upon receiving a bad signal, the planner knows with certainty that the worker deviated from the recommended level of effort. This event, regardless of its probability, can be leveraged as much as needed to provide the incentives for the worker to exert the high level of effort.

I now move to the effect of the worker's state on the monitoring frequency and the spread of future consumption. The proof is inspired by Newman (2007).

Proposition 1 *The optimal monitoring frequency increases with U.*

Proof. I first show that $M(U, \mu)$ is supermodular in U, μ. For a twice differentiable function, this is equivalent to showing that $\frac{\partial^2 M(U,\mu)}{\partial U \partial \mu} \geq 0$.

Since λ_1 is the shadow price of the promised utility constraint $\frac{\partial M(U,\mu)}{\partial U}$ is equal to λ_1; therefore the supermodularity condition becomes:

$$\frac{\partial^2 M(U,\mu)}{\partial U \partial \mu} = \frac{\partial \left\{ \frac{\partial M(U,\mu)}{\partial U} \right\}}{\partial \mu} = \frac{\partial \lambda_1}{\partial \mu}$$

From Lemma 2 λ_1 equals $\frac{-\pi c^e - (1-\pi)\left\{(1-\mu)c^n + \mu\left[\theta_h c^g + (1-\theta_h)c^b\right]\right\} - c}{2}$ and therefore:

$$\frac{\partial^2 M(U,\mu)}{\partial U \partial \mu} = \frac{\partial \left\{ \frac{-\pi c^e - (1-\pi)\left\{(1-\mu)c^n + \mu\left[\theta_h c^g + (1-\theta_h)c^b\right]\right\} - c}{2} \right\}}{\partial \mu}$$

Note that $\frac{-\pi c^e - (1-\pi)\left\{(1-\mu)c^n + \mu\left[\theta_h c^g + (1-\theta_h)c^b\right]\right\} - c}{2}$ is the total cost for the planner providing that level of utility **excluding the monitoring cost.** Since the monitoring cost is excluded, the cost of providing utility cannot increase when monitoring increases.[28] Therefore: $\frac{\partial \left\{ \frac{-\pi c^e - (1-\pi)\left\{(1-\mu)c^n + \mu\left[\theta_h c^g + (1-\theta_h)c^b\right]\right\} - c}{2} \right\}}{\partial \mu} \geq 0$, and supermodularity between U and μ holds.

Supermodularity implies that increasing one variable enlarges the returns from increasing the other variables (Athey, 2002). In the monitoring context, supermodularity implies that increasing the promised utility improves the return to monitoring. Therefore, as long as the first-order condition with respect to the monitoring frequency holds for $V(U)$, the monitoring frequency increases with promised utility. ■

Monitoring frequency is one of the two instruments of monitoring policy. The second instrument is the choice of the planner to spread out future utilities (henceforth, spreads). To simplify the discussion define the spreads as positive ones as follows: The spread between promised utility of outcomes $\{i,j\} \in \{e,n,g,b\}$ is $u(c^i) - u(c^j)$ such that $c^i \geq c^j$. The next main result, Proposition 2, complements the first by showing that as promised

[28] Denote the initial monitoring probability with μ_1 and the new higher probability by $\mu_2 > \mu_1$. The planner can ignore the additional information by using a lottery on the monitoring application with weight $\delta = \frac{\mu_1}{\mu_2}$. When monitoring is applied (with probability μ_2) the planner will use the same allocation given μ_1 with probability δ, and the allocation given that monitoring was not applied with probability $1-\delta$.

utility increases, the spreads decrease. The next Lemma provides an important building block for this result :

Lemma 3 *When either μ or U, or both, change, all the spreads move in the same direction.*

Proof. Let $\left\{c_1^i, c_1^j, c_1^k, c_1^l\right\}, \left\{c_2^i, c_2^j, c_2^k, c_2^l\right\}$ be the optimal consumption levels for $\{U_1, \mu_1\}, \{U_2, \mu_2\}$, respectively, and assume without loss of generality that $\frac{c_1^i}{c_1^j} \geq \frac{c_2^i}{c_2^j}$, i.e., that the spread associated with outcomes $\{i, j\}$ is larger when $\{U, \mu\} = \{U_1, \mu_1\}$. Using the first-order conditions $\frac{c^i}{c^j} = \frac{\lambda_1 + \lambda_2 l^i}{\lambda_1 + \lambda_2 l^j}$. Therefore: $\frac{\lambda_1^1 + \lambda_2^1 l^i}{\lambda_1^1 + \lambda_2^1 l^j} \geq \frac{\lambda_1^2 + \lambda_2^2 l^i}{\lambda_1^2 + \lambda_2^2 l^j}$. After multiplying by both denominators (note that $\left(-c_1^j\right)\left(-c_j^j\right) = c_1^j c_j^j > 0$) and rearranging we get that: $\lambda_2^1 \lambda_1^2 - \lambda_1^1 \lambda_2^2 \geq 0$. By repeating the same steps backwards for any j, k, we get that: $\frac{c_1^k}{c_1^l} \geq \frac{c_2^k}{c_2^l}$, with strict inequality if $\frac{c_1^i}{c_1^j} > \frac{c_2^i}{c_2^j}$.

Since $u(c^i) - u(c^j) = \log(\frac{c^i}{c^j})$, if one spread decreases, then the rest of the spreads must decrease as well. ■

Proposition 2 *The spreads decrease with promised utility.*

Proof. Rewrite the incentive-compatibility constraint as a linear combination of spreads.

$$\pi[u(c^e) - u(c^g)] + \pi(1-\mu)[u(c^g) - u(c^n)] + \mu(\pi(1-\theta_h) + \theta_h - \theta_l)[u(c^g) - u(c^b)] = e. \quad (9)$$

Using (9), the effect of an increase in the monitoring probability on the left-hand side of the constraint can be written as:

$$\pi[u(c^n) - u(c^b) - \theta_h\left(u(c^g) - u(c^b)\right)] + (\theta_h - \theta_l)[u(c^g) - u(c^b)]$$

The right-hand term is strictly positive because $\theta_h > \theta_l$ and $c^g > c^b$. Therefore, the total effect of the increase in the monitoring frequency on the left-hand side is strictly positive if the first term is non-negative. For log utility, this is equivalent to showing that:

$$\log(c^n) > \theta_h \log(c^g) + (1 - \theta_h) \log(c^b)$$

Since at the optimum, $c^n = \theta_h c^g + (1 - \theta_h)c^b$ (see Lemma 2 above), the inequality above holds as the logarithmic function is a concave transformation of $f(c) = c$.

Hence, following an increase in μ, at least one spread must decrease to keep the constraint tight; by Lemma 3 all the spreads drop together.

Since we know from Proposition 1 that an increase in U leads to an increase in the monitoring frequency, and since an increase in the monitoring frequency leads to a decrease in the spreads, it follows that an increase in U also leads to a decrease in the spreads.[29]

■

Note that together with Lemma 3, condition (9) implies that if the monitoring frequency is constant, then all spreads are constant as well. This is so because the coefficients of all spreads in (9) are all positive, and they can only move in the same direction.

Taken together, the two above propositions suggest that as the promised utility of the worker increases, the planner monitors the unemployed more frequently but imposes more moderate sanctions. Note that this result holds for any parametrization of the model as long as utility from consumption is logarithmic.

[29] Equation (9) also shows that U may affect the spreads only when there is a change in μ. This rules out combined effects such as a decrease in the spreads due to the increase in the monitoring probability and the independent increase in the spread following a change in U.

APPENDIX B: COMPUTATIONAL METHOD

This appendix describes the solution method for the problem of a planner who recommends the high job-search effort during unemployment.[30]

Transform the maximization problem with six decision variables and two constraints into a maximization problem with four decision variables and no constraints. Write the incentive-compatibility constraint as follows:[31]

$$\begin{aligned} & u(c) - e + \beta \pi U^e + \beta (1-\pi) \left[(1-\mu) U^n + \mu \left(\theta_h U^g + (1-\theta_h) U^b \right) \right] \\ = \quad & u(c) + \beta \left[(1-\mu) U^n + \mu \left(\theta_l U^g + (1-\theta_l) U^b \right) \right] \end{aligned}$$

and express U^e in terms of U^n, U^g, U^b and μ :

$$U^e = \frac{e}{\beta\pi} + (1-\mu) U^n - \frac{\mu}{\pi} \left\{ \left[(1-\pi)\theta_h - \theta_l \right] U^g + \left[(1-\pi)(1-\theta_h) - (1-\theta_l) \right] U^b \right\} \qquad (10)$$

Use the promise keeping constraint to express c in terms of U^e, U^n, U^g, U^b and μ :

$$c = u^{-1} \left\{ U + e - \beta \left[\pi U^e + (1-\pi) \left((1-\mu) U^n + \mu \left(\theta_h U^g + (1-\theta_h) U^b \right) \right) \right] \right\} \qquad (11)$$

Use (10) in the right-hand side of (11) to express the consumption level (c) in terms of U^n, U^g, U^b and μ. Substitute this value of c and the value for U^e from (10) into (2) to receive the maximization problem with four decision variables: U^n, U^g, U^b and μ, with no constraints.

Those four remaining decision variables consist of three continuation values (U^n, U^g, U^b) and the monitoring frequency μ. While the support for the continuation values is the real line, the support for the monitoring frequency is $[0, 1]$. This closed support presents a computational challenge, which I overcome by distcritizing the support of the monitoring

[30] In absence of asymmetric information, the solution to the employment problem consists of constant benefits for the complete duration of employment.

[31] In the optimal solution, the incentive compatibility constraint always holds with equality. This is the case because delivering an expected discounted utility that is higher than the required one, costs more.

frequency into 151 values and then solve the maximization problem for each of those 151 values.[32]

Thus, the maximization problem is reduced to three continuous variables: U^n, U^g, U^b. The solution to this problem is based on the three first-order conditions with respect to U^n,U^g, and U^b respectively:

$$\left(u^{-1}\right)'(c\_\arg) + \pi W'(U^e) + (1-\pi)V'(U^n) = 0$$

$$\left(u^{-1}\right)'(c\_\arg)(1-\theta_l) - W'(U^e)((1-\pi)\theta_h - \theta_l) + (1-\pi)\theta_h V'(U^g) = 0$$

$$\left(u^{-1}\right)'(c\_\arg)\theta_l - W'(U^e)((1-\pi)(1-\theta_h) - (1-\theta_l)) + (1-\pi)(1-\theta_h)V'(U^b) = 0$$

where I have defined for brevity of notation:

$$c\_\arg = U + e - \beta\left[\pi U^e + (1-\pi)\left((1-\mu)U^n + \mu\left(\theta_h U^g + (1-\theta_h)U^b\right)\right)\right]$$

These equations are solved over a grid of $\{U, \mu\}$ with 600 and 151 values respectively. The value for $V(U)$ is then the maximum value of V for a given U over all possible levels of monitoring probability.

[32] The sensitivity of the solution is, therefore, 0.0033 of monitoring frequency.

APPENDIX C: THE MONITORING PROBABILITY IN THE US

The calibration of the actual monthly monitoring probability in the US, μ^{ACT}, is based on the frequency of required reports of employment contacts that the unemployed workers fill in and on the probability that these contacts are verified. While the weekly frequency of reports is fairly consistent across states (O'Leary 2004), the probability or verifying these contacts varies vastly across states: some states (e.g. Pennsylvania) do not monitor at all; some states (e.g. Washington) have a target monitoring frequency of 10%; and some states (e.g. South Dakota) consistently review contacts every 4-6 weeks (DOL 2003).

For the probability of verifying employment contacts in the US, I use a conservative value of 5% (the lower this probability the lower is θ_h). This value determines, together with a weekly frequency of reports, a monthly monitoring probability $\left(\mu^{ACT}\right)$ of 20%.[33]

[33] The unemployed worker submits $52/12 = 4\frac{1}{3}$ reports a year. The probability of being monitored at least once in a month is: $1 - 0.95^{4.33} = 0.20$, where 0.95 is the probability of not being monitored in a given week.

APPENDIX D: PROOFS

Claim 1 $\frac{\partial^2 V(U)}{\partial \mu^2} < 0$

Proof. Use the promise keeping and incentive-compatibility constraints to derive c, and U^e as a function of U^g, U^n, U^b and μ.

$$\begin{aligned} U^e &= \frac{e}{\pi\beta} + (1-\mu) U^n + \frac{\mu}{\pi}\left\{\left[\left(\theta_l U^g + (1-\theta_l) U^b\right)\right] - (1-\pi)\left[\left(\theta_h U^g + (1-\theta_h) U^b\right)\right]\right\} \\ c &= u^{-1}\left[U - \beta\left[(1-\mu) U^n + \mu\left(\theta_l U^g + (1-\theta_l) U^b\right)\right]\right] \end{aligned}$$

Substitute the constraints into the maximization problem:

$$\begin{aligned} V(U) &= \max_{U^g, U^b, U^n, \mu} -\kappa\mu^\alpha - u^{-1}\left[U - \beta\left[(1-\mu) U^n + \mu\left(\theta_l U^g + (1-\theta_l) U^b\right)\right]\right] \\ &+\beta\left\{\begin{array}{c} \pi W(\frac{e}{\pi\beta} + (1-\mu) U^n + \frac{\mu}{\pi}\left\{\left[\left(\theta_l U^g + (1-\theta_l) U^b\right)\right] - (1-\pi)\left[\left(\theta_h U^g + (1-\theta_h) U^b\right)\right]\right\}) \\ +(1-\pi)\left\{(1-\mu) V(U^n) + \mu\left[\theta_h V(U^g) + (1-\theta_h) V(U^b)\right]\right\} \end{array}\right\} \end{aligned}$$

Differentiate twice with respect to μ :

$$\begin{aligned} \frac{\partial^2 V(U)}{\partial \mu^2} = - \quad & c * \left[-\beta\left(-U^n + \left(\theta_l U^g + (1-\theta_l) U^b\right)\right)\right]^2 + \beta\pi W''\{U^e\} * \\ & \left[-U^n + \frac{1}{\pi}\left\{\left[\left(\theta_l U^g + (1-\theta_l) U^b\right)\right] - (1-\pi)\left[\left(\theta_h U^g + (1-\theta_h) U^b\right)\right]\right\}\right]^2 - \\ & \alpha(a-1)\kappa\mu^{\alpha-2}, \end{aligned}$$

which is strictly negative for every $\alpha \leq 1$ since u^{-1} is convex and W is concave. Note that since the first two terms are strictly negative for any α, the claim also holds for some convex cost of monitoring. ■

TABLES AND FIGURES

TABLE 1
Calibration parameters

Parameter	**Symbol**	**Value**	**Source**
Discount factor	β	0.9959	Cooley (1995)
Wage	w	\$2,800	National compensation survey (2006)
Unemployment exit rate	π	0.17	Shimer (2007)
Disutility from effort	e	0.67	Pavoni and Violante (2007)
Good signal probability given **high** effort	θ_h	0.98	See text
Good signal probability given **bad** effort	θ_l	0.08	See text
Monitoring cost	κ	\$30	See text
Monitoring cost curvature	α	1.0	See text

TABLE 2
Sensitivity analysis of ν for the value of θ_h

θ_h	0.90	0.95	**0.98**	0.99	1.00
ν	0.61	0.72	**0.82**	0.87	1.00

TABLE 3
Sensitivity analysis of ν for the value of θ_l

θ_l	0.0	**0.08**	0.30	0.50	0.80
ν	0.84	**0.82**	0.77	0.70	0.35

TABLE 4
Sensitivity analysis of ν for the value of κ

κ (\$)	0	10	**30**	50	100
ν	0.99	0.89	**0.82**	0.77	0.70

TABLE 5
Sensitivity analysis of ν for the value of α

α	0.2	0.5	**1.0**	2	5
ν	0.37	0.6	**0.82**	0.93	0.96

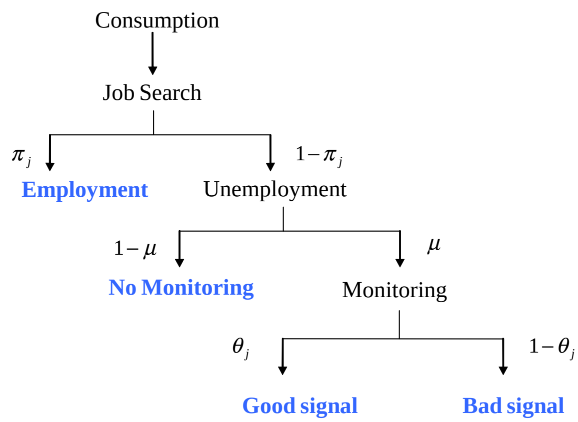

Fig. 1. The timing of the model and the four possible end-of-period outcomes: employment, unmonitored unemployment, monitored unemployment with a good signal, and monitored unemployment with a bad signal.

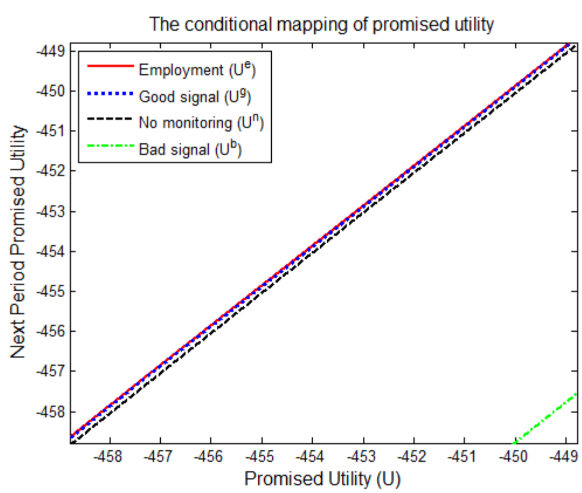

Fig. 2. The mapping of promised utility from the current period to the next period, conditioned on the four possible outcomes: employment, unmonitored unemployment, monitored unemployment with a good signal, and monitored unemployment with a bad signal. The values for employment and monitoring with a good signal are above the diagonal (the diagonal itself is not illustrated) with the one for the good signal only slightly below the one for employment. The value for unmonitored unemployment is only slightly below the diagonal. Finally, the value for monitored unemployment with a bad signal is significantly below the diagonal.

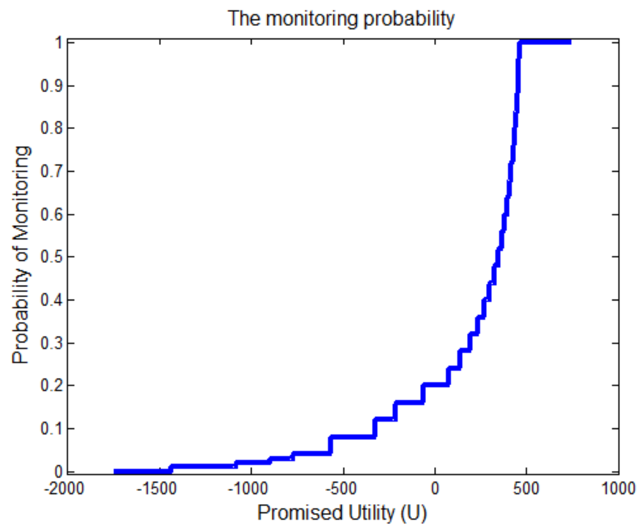

Fig. 3. The monitoring frequency by promised utility. As the generosity of the welfare system increases, the monitoring frequency increases and the relative consumption sanction (Fig. 4) decreases.

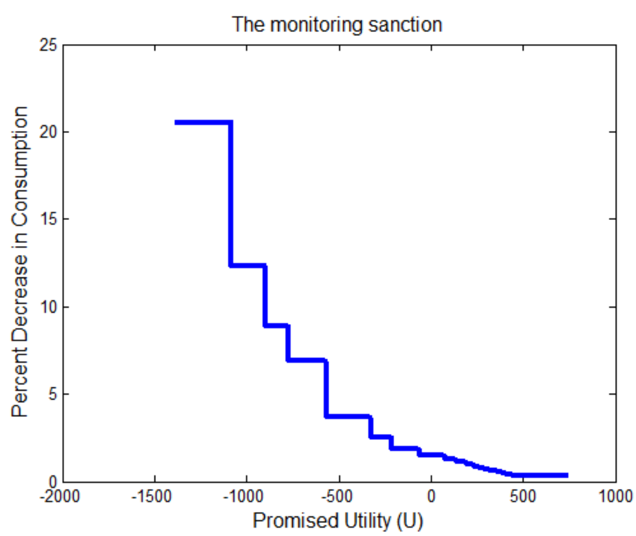

Fig. 4. The relative consumption sanction by promised utility. The sanction responds to changes in the monitoring frequency (Figure 3). Note that when the monitoring frequency is constant, so is the sanction.

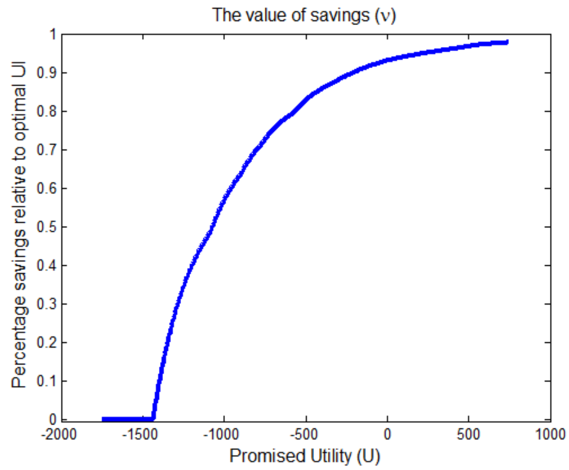

Fig. 5. The value of monitoring as the fraction of moral-hazard cost associated with optimal unemployment insurance that is saved when the monitoring technology is available.

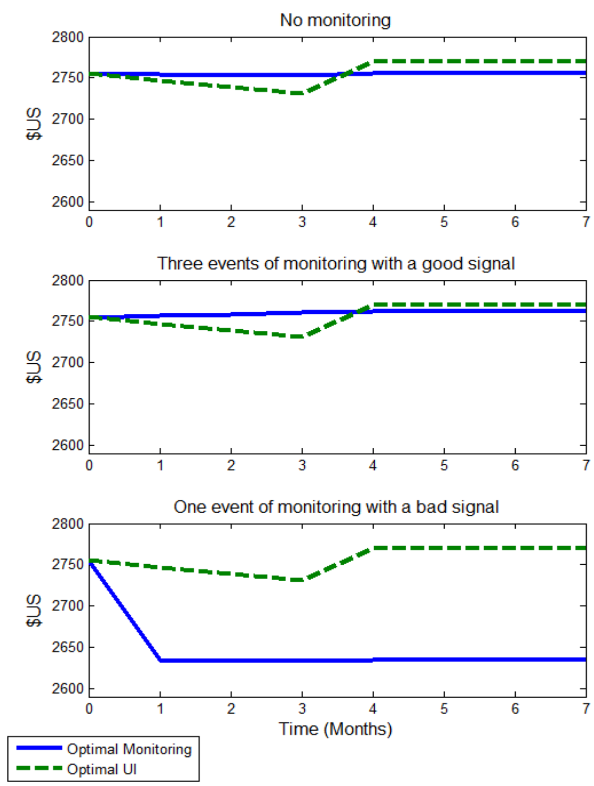

Fig. 6. Simulated consumption paths according to optimal monitoring and optimal unemployment insurance policies. The consumption paths for the unemployment insurance policy are identical. The consumption paths for the monitoring policy depend on whether monitoring was applied and the signal's result.

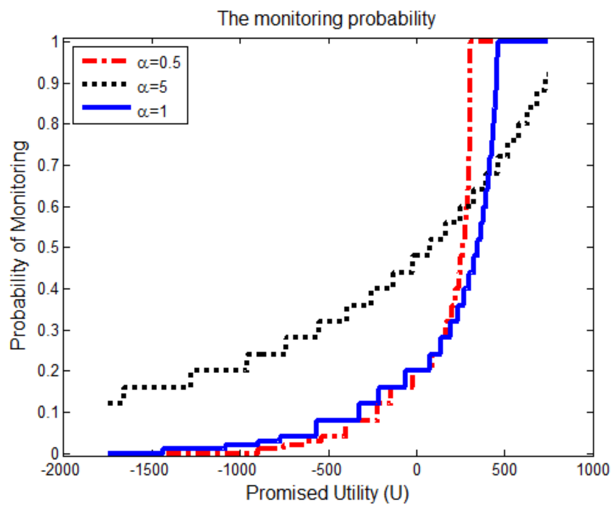

Fig. 7. Monitoring frequency for various monitoring cost types. As the cost becomes more convex (alpha increases) the marginal cost of monitoring increases and the increase in monitoring becomes more moderate.

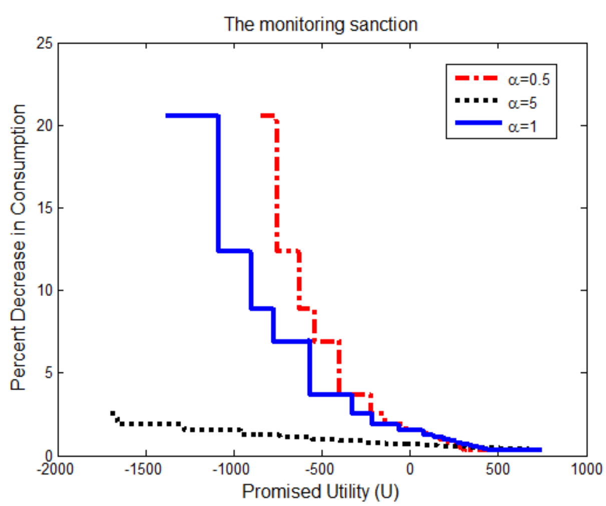

Fig. 8. The relative consumption sanction for various monitoring cost types. The spreads change according to the monitoring frequency (Fig. 7).