Chapter 2
Incentive Mechanisms for Multi-agent Organizational Systems

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Abstract This work considers game-theoretic models of incentive mechanisms for multi-agent organizational systems. Three main principles of optimal incentive scheme design for interacting agents are derived, namely, the principle of compensation, the principle of decomposition and the principle of aggregation. Models of agents' self-coordination are explored in terms of side-payoff games. And finally, we study identification problems for agents' preferences.

An incentive means motivation of a subject to perform specific actions; in organizational systems, a *Principal* stimulates an *agent* by exerting an impact on its preferences (i.e., a goal function) (Novikov 2013a).

Interests' coordination between a Principal and agents is not a trivial problem. This fact was realized at the turn of the 1960–1970s, when theory of contracts appeared. Among the pioneering results, we mention the Azariadis-Baily-Gordon (ABG) model (Azariadis 1975; Baily 1974; Gordon 1974) which intended to explain the difference between efficient (predicted by labor economics) and observed wage levels–see the survey (Hart and Holmstrom 1987).

The parallel and intensive development of mechanisms theory in the 1970–1990s, namely:

- *contract theory* (CT) by Grossman and Hart (1983), Hart (1983), Mookherjee (1984), Myerson (1982), Salanie (2005) and others,
- *theory of active systems* (TAS) by Burkov (1977), Burkov et al. (1993, 2015), Burkov and Enaleev (1994), Novikov (1997) and others,

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- *theory of hierarchical games* (THG) by Germeier Yu (1986), Germeier (1971), Kononenko (1977), Kukushkin (1972) and others,[1]

yielded the fruitful and diversified theory of mathematical models of incentives in organizations (see the overview Burkov et al. 1993), as well as the monographs and textbooks (Bolton and Dewatripont 2005; Laffont and Martimort 2001; Novikov 2013a, c; Salanie 2005; Stole 1997).

This chapter describes in brief the state-of-the-art of the individual and collective incentive mechanisms for multi-agent organizational systems (OSs).

2.1 Individual Incentive Mechanisms

Let $N = \{1, 2, \ldots, n\}$ be a set of agents, $y_i \in A_i$ stand for an *action* of agent i, and $c_i\,(y)$ mean its *costs*. By assumption, costs functions are monotonic and nonnegative, $c_i\,(0) = 0$—see the details below. Moreover, denote by $\sigma_i\,(y)$ a reward given by a Principal to agent i ($i \in N$); accordingly, $y = (y_1, y_2, \ldots, y_n)$ represents an action profile of all agents, $y \in A' = \prod_{i \in N} A_i$. Suppose that the Principal gains an income $H(y)$ from agents' activity. Hence, the Principal's goal function acquires the form

$$\Phi(\sigma(\cdot), y) = H(y) - \sum_{i \in N} \sigma_i(y)\,, \tag{2.1}$$

where $\sigma(\cdot) = (\sigma_1(y), \ldots, \sigma_n(y))$ forms the vector of individual rewards and the goal function of agent i is

$$f_i(\sigma_i(\cdot), y) = \sigma_i(y) - c_i(y). \tag{2.2}$$

If agent's reward depends generally on the actions of all agents, the incentive scheme is called *collective*. Special cases include *individual rewards* ($\sigma_i = \sigma_i(y_i)$) and uniform rewards ($\sigma_i = \sigma_0(y_i)$).

An elementary extension of the basic single-agent model (Novikov 2013c) concerns a *multi-agent OS* with independent (noninteracting) agents. In this case, the incentive problem is decomposed into a set of corresponding single-agent problems.

Suppose that identical constraints are imposed on the incentive mechanism for all agents or a certain subset of agents. As a result, we derive the incentive problem in an *OS with weakly related agents* (discussed below). This problem represents a

[1] In short, these three scientific schools differ in the following. TC analyzes incentives under stochastic uncertainty when an agent is risk-averse (i.e., has a concave utility function). In TAS, agents are typically considered risk-neutral, but much attention belongs to incentives' compatibility and applications. And finally, THG focuses mostly on mathematical aspects and dynamic models.

set of parametric single-agent problems, and it is possible to search for optimal parameter values using standard constrained optimization techniques.

If agents are interrelated, viz., the costs or/and rewards of an agent depend on its actions and the actions of the rest agents, one obtains a “full-fledged” multi-agent incentive model. It will be studied in the present section.

The solution procedures of the multi- and single-agent problems have much in common. At the beginning, one has to apply the **principle of compensation**, i.e., to construct a *compensatory incentive scheme* (Novikov 2013c) implementing a certain action (an arbitrary feasible action under given constraints). In fact, this is Stage 1 known as *incentives’ compatibility analysis*. Put forward the *hypothesis of benevolence*: if the agent is choice-indifferent, it chooses the action beneficial to the Principal. Then in single-agent OSs it suffices to verify that the maximum of the agent’s goal function is attainable by an implementable action. On the other hand, in multi-agent systems one should demonstrate that the choice of a corresponding action makes up an *equilibrium strategy* in the game of agents. Imagine that there exist several equilibria; in this case, we have to verify the hypothesis of *rational choice* for the action in question. In most situations, it takes only to accept the *unanimity axiom* (according to the latter, agents do not choose equilibria dominated by other equilibria in the sense of Pareto). Sometimes, the Principal has to evaluate its *guaranteed result* on the set of equilibrium strategies of agents, and so on. Further, it is necessary to equate the incentive and the costs and solve a standard optimization problem: find an implementable action to-be-rewarded by the Principal. Actually, this is Stage 2 known as *incentive-compatible planning* (Burkov et al. 2015; Novikov 2013c). Let us describe the above approach in detail.

Incentives in OSs with weakly related agents. Let (a) agents’ goal functions depend only on their individual actions (the so-called *separable costs*), (b) the incentive of each agent depend on its individual actions exclusively, and (c) some constraints be imposed on the total incentive of all agents. The formulated model is an *OS with weakly related agents*. As a matter of fact, this is an intermediate case between individual and collective incentive schemes.

Suppose that the individual rewards of agents are majorized by the quantities $\{C_i\}_{i \in N}$; in other words, $\forall\, y_i \in A_i$: $\sigma_i\,(y_i) \leq C_i$, $i \in N$. In addition, the *wage fund* (WF) has an upper bound R: $\sum_{i \in N} C_i \leq R$. Then the maximal *set of implementable actions* of agent i depends on the corresponding constraint R of the incentive mechanism: $P_i(C_i) = [0; y_i^+(C_i)]$, where

$$y_i^+(C_i) \;=\; \max\,\{y \in A_i | c_i(y) \leq C_i\}, i \,\in\, N.$$

Consequently, the optimal solution to the incentive problem in an OS with weakly related agents is defined as follows. One has to maximize the function

$$G(R) = \max_{\{y_i \in P_i(C_i)\}_{i \in N}} H(y_1,\, \ldots, y_n)$$

by an appropriate choice of the individual constraints $\{C_i\}_{i \in N}$ satisfying the *budget constraint* $\sum_{i \in N} C_i \le R$. Apparently, this is a standard constrained optimization problem.

For a fixed WF, the agent's costs are not extracted from its income. At the same time, in the case of a variable WF, the optimal value R^* makes a solution to the following optimization problem:

$$R^* = \arg\max_{R \ge 0}\, [G(R) - R].$$

Incentives in OSs with strongly related agents. For agent i, designate by $y_{-i} = (y_1, y_2, \ldots, y_{i-1}, y_{i+1}, \ldots, y_n) \in A_{-i} = \prod_{j \ne i} A_j$ its opponents' action profile.

In the incentive model (2.1) and (2.2), the individual incentive and the individual costs of agent i to choose the action y_i generally depend on the actions of all agents.

Adopt the following sequence of moves in the OS. At the moment of their decision-making, the Principal and agents know the goal functions and feasible sets of all OS participants. Enjoying the right of the first move, the Principal chooses incentive functions and reports them to the agents. Next, under known incentive functions, agents simultaneously and independently choose their actions to maximize appropriate goal functions.

We make a series of assumptions on different parameters of the OS:

(1) for each agent, the set of feasible actions coincides with the set of nonnegative real values;
(2) the cost functions of agents are continuous and nonnegative; moreover, $\forall\, y_i \in A_i : c_i\,(y)$ does not decrease in y_i and $\forall\, y_{-i} \in A_{-i} : c_i\,(0, y_{-i}) = 0$ $(i \in N)$;
(3) the Principal's income function is continuous with respect to all arguments and attains the maximum for nonzero actions of agents.

In essence, Assumption 2 implies that (regardless of the actions of the rest agents) any agent can minimize its costs by choosing an appropriate (zero) action.

The costs and incentive of each agent generally depend on the actions of all agents. Hence, agents get involved in a *game*, where the payoff of each agent depends on the actions of all opponents. Suppose that $P(\sigma)$ is the *set of equilibrium strategies* of agents under the incentive scheme $\sigma(\cdot)$ (actually, this is the set of game solutions). For the time being, we do not specify the type of equilibrium, only presumming that agents choose their strategies simultaneously and independently. Thus, they do not interchange information and utility.

The guaranteed efficiency (or simply "*efficiency*") of an incentive scheme represents the minimum value (within the hypothesis of benevolence, the maximum value) of the Principal's goal function over the corresponding set of game solutions:

$$K(\sigma) = \min_{y \in P(\sigma)} \Phi(\sigma, y). \tag{2.3}$$

Under a given set M of feasible incentive schemes, the problem of *optimal incentive function/scheme design* lies in searching for a feasible incentive scheme σ^* which maximizes the efficiency:

$$\sigma^* = \arg\max_{\sigma \in M} K(\sigma). \tag{2.4}$$

In the special case of independent agents (i.e., the reward and costs of each agent get predetermined by its actions only), the *compensatory incentive scheme* (Novikov 2013c)

$$\sigma_{iK}(y_i) = \begin{cases} c_i(y_i^*) + \delta_i, & y_i = y_i^* \\ 0, & y_i \neq y_i^* \end{cases}, i \in N, \tag{2.5}$$

appears optimal (to be correct, δ-optimal, where $\delta = \sum_{i \in N} \delta_i$). In the formulas above, $\{\delta_i\}_{i \in N}$ designate arbitrarily small strictly positive constants (bonuses). Moreover, the optimal action y^*, being implementable by the incentive scheme (2.5) as a *dominant strategy equilibrium*[2] (DSE), solves the following problem of optimal incentive-compatible planning:

$$y^* = \arg\max_{y \in A'} \{H(y) - \sum_{i \in N} c_i(y_i)\}.$$

Suppose that the reward of each agent depends on the actions of all agents (this is exactly the case for collective incentives studied here) and the *costs are inseparable* (i.e., the costs of each agent generally depend on the actions of all agents, reflecting their interrelation). Then the sets of *Nash equilibria*[3] $E_N(\sigma) \subseteq A'$ and DSE $y_d \in A'$ acquire the form

$$E_N(\sigma) = \{y^N \in A \mid \forall i \in N \, \forall \, y_i \in A_i, \tag{2.6}$$

$$\sigma_i(y^N) - c_i(y^N) \geq \sigma_i(y_i, y_{-i}^N) - c_i(y_i, y_{-i}^N)\}.$$

By definition, $y_{i_d} \in A_i$ is a *dominant strategy* of agent i iff

$$\forall y_i \in A_i, \forall y_{-i} \in A_{-i}:$$

$$\sigma_i(y_{i_d}, y_{-i}) - c_i(y_{i_d}, y_{-i}) \geq \sigma_i(y_i, y_{-i}) - c_i(y_i, y_{-i}).$$

[2] Recall that a DSE is an action vector such that each agent benefits from choosing a corresponding component regardless of the actions chosen by the rest agents.

[3] A Nash equilibrium is an action vector such that each agent benefits from choosing a corresponding component provided that the rest agents choose equilibrium actions.

Imagine that a dominant strategy exists for each agent under a given incentive scheme. In this case, the incentive scheme is said to implement the corresponding action vector as a DSE.

Fix an arbitrary action vector $y^* \in A'$ of agents and consider the following incentive scheme:

$$\sigma_i(y^*, y) = \begin{cases} c_i(y_i^*, y_{-i}) + \delta_i, & y_i = y_i^* \\ 0, & y_i \neq y_i^* \end{cases}, \delta_i \geq 0, i \in N. \tag{2.7}$$

It was shown in Novikov and Tsvetkov (2001) that the vector y^* forms a DSE under the incentive scheme (2.7) applied by the Principal. Moreover, if $\delta_i > 0$, $i \in N$, then y^* makes up a unique DSE.

The *collective incentive scheme* (7) means that the Principal adopts the **principle of decomposition**. It suggests to agent i, "Choose the action y_i^*, and I compensate your costs regardless of the actions chosen by the rest agents. Yet, if you choose another action, the reward is zero." Using such strategy, the Principal decomposes the game of agents.

Assume that the incentive of each agent depends implicitly on its action only. By fixing the opponents' action profile for each agent, pass from (2.7) to *an individual incentive* scheme. Notably, fix an arbitrary action vector $y^* \in A'$ of agents and define the incentive scheme

$$\sigma_i(y^*, y_i) = \begin{cases} c_i(y_i^*, y_{-i}) + \delta_i, & y_i = y_i^* \\ 0, & y_i \neq y_i^* \end{cases}, \quad \delta_i \geq 0, i \in N. \tag{2.8}$$

In this case, we have the following interpretation. The Principal suggests to agent i, "Choose the action y_i^*, and I compensate your costs as if the rest agents would have chosen the corresponding actions y_{-i}^*. Yet, if you choose another action, the reward is zero." Adhering to such strategy, the Principal also decomposes the game of agents, i.e., implements the vector y^* as a Nash equilibrium of the game.

Interestingly, the incentive scheme (2.8) depends only on the action of agent i, while y_{-i}^* enters this function as a parameter. Moreover, in contrast to the incentive scheme (2.7), the incentive scheme (2.8) provides each agent merely with indirect information about the action vector desired by the Principal. For the incentive scheme (2.8) to implement the vector y^* as a DSE, additional assumptions should be introduced regarding the cost functions of agents, see Novikov and Tsvetkov (2001). This is not the case for the incentive scheme (2.7).

It seems quite appropriate here to discuss the role of $\{\delta_i\}_{i \in N}$ in the expressions (2.5), (2.7) and (2.8). If one needs implementing a certain action as a Nash equilibrium, these constants can be chosen zero. Imagine that the equilibrium must be unique (in particular, agents are required not to choose zero actions; otherwise, in evaluation of the guaranteed result (2.3) the Principal would be compelled to expect zero actions of agents). In this case, agents should be paid excess an arbitrarily small (strictly positive) quantity for choosing the action expected by the Principal.

Furthermore, the parameters $\{\delta_i\}_{i \in N}$ in formulas (2.5), (2.7) and (2.8) appear relevant in the sense of stability of the compensatory incentive scheme with respect to the model parameters. For instance, suppose that we know the cost function of agent i up to some constant $\Delta_i \leq \delta_i / 2$. Consequently, the compensatory incentive scheme (2.7) still implements the action y^*, see Novikov and Tsvetkov (2001).

The vector of optimal implementable actions y^*, figuring in the expression (2.7) or (2.8) as a parameter, results from the following *problem of optimal incentive-compatible planning*:

$$y^* = \arg\{\max_{t \in A'}\{H(t) - v(t)\}, \tag{2.9}$$

where $v(t) = \sum_{i \in N} c_i(t)$, and the efficiency of the incentive scheme (2.7), (2.9) constitutes

$$K^* = H(y^*) - \sum_{i \in N} c_i(y^*) - \delta.$$

It was demonstrated in Novikov and Tsvetkov (2001) that the incentive scheme (2.7), (2.9) appears *optimal*, i.e., possesses the maximum efficiency among all incentive schemes in multi-agent OSs.

An interested reader can find some examples of designing optimal collective incentive schemes for multi-agent OSs in the book (Novikov 2013c).

We have finished the discussion of incentive mechanisms for individual results of agents' activity. To proceed, let us describe some collective incentive mechanisms.

2.2 Collective Incentive Mechanisms

The majority of well-known incentive models consider two types of OSs. The first type is when a Principal observes the result of activity for all agents, being uniquely defined by their actions. The second type includes OSs with *uncertainties*, where the observed result of agents' activity depends not only on their actions, but also on uncertain and/or random factors (e.g., see the survey and models in Novikov 2013a, c).

The present section provides the statement and solution to the collective incentive problem in a multi-agent deterministic OS, where a Principal possesses only some aggregated information about the results of agents' activity.

In an n-agent OS, let the *result of agents' activity* $z \in A_0 = Q(A')$ be a certain function of their actions: $z = Q(y)$. In this case, $Q(\cdot)$ is termed the *aggregation function*. The preferences of OS participants, i.e., the Principal and agents, are expressed by their goal functions. In particular, the Principal's goal function makes up the difference between its income $H(z)$ and the total incentive $\upsilon(z)$ paid to agents:

$\upsilon(z) = \sum_{i \in N} \sigma_i(z)$. Here $\sigma_i\ (z)$ stands for the incentive of agent i, $\sigma\ (z) = (\sigma_1(z), \sigma_2(z), \ldots, \sigma_n\ (z))$, i.e.,

$$\Phi(\sigma(\cdot), z) = H(z) - \sum_{i \in N} \sigma_i(z). \tag{2.10}$$

The goal function of agent i represents the difference between the reward given by the Principal and the costs $c_i\ (y)$:

$$f_i(\sigma_i(\cdot), y) = \sigma_i(z) - c_i(y), i \in N. \tag{2.11}$$

We adopt the following sequence of moves in the OS. At the moment of decision-making, the Principal and agents know the goal functions and feasible sets of each other, as well as the aggregation function. The Principal's strategy is assigning incentive functions, while agents choose their actions. Enjoying the right of the first move, the Principal chooses incentive schemes and report them to agents. Under known incentive functions, agents subsequently choose their actions by maximizing the corresponding goal functions.

Imagine that the Principal observes the individual actions of agents (equivalently, the Principal can uniquely recover the actions using the observed result of activity). Then the Principal may employ an incentive scheme being directly dependent on the agents' actions: $\forall\ i \in N$: $\tilde{\sigma}_i(y) = \sigma_i\ (Q(y))$. We refer to the previous section for the detailed treatment of such incentive problems. Therefore, our analysis focuses on a situation when the Principal observes merely the result of activity in the OS (which predetermines the Principal's income). It is unaware of the individual actions of agents and cannot restore this information. In other words, *aggregation of information* takes place–the Principal possesses incomplete information on the agents' action vector $y \in A'$. It knows just some aggregated rate $z \in A_0$ (a parameter characterizing the results of agents' joint actions).

In the sequel, we believe that the OS parameters meet the assumptions from the previous section. Moreover, suppose that the aggregation function is a one-valued continuous function.

By analogy to the aforesaid, the efficiency of incentive is comprehended as the minimum value (or the maximum value–under the hypothesis of benevolence) of the Principal's goal function on the solution set of the game:

$$K(\sigma(\cdot)) = \min_{y \in P(\sigma(\cdot))} \Phi(\sigma(\cdot), \mathrm{Q}(y)). \tag{2.12}$$

The problem of optimal incentive function design lies in searching for a feasible incentive scheme σ^* maximizing the efficiency:

$$\sigma^* = \arg\max_{\sigma(\cdot)} k(\sigma(\cdot)). \tag{2.13}$$

The decomposition of the agents' game in the previous section bases on the Principal's ability to motivate agents for choosing a specific (observable!) action. Under unobservable actions of agents, direct application of the decomposition principle seems impossible. Thus, solution of the incentive problems (where agents' rewards depend on the observed aggregated result of activity) should follow another technique.

This technique is rather transparent. Find a set of actions yielding a given result of activity. Then separate a subset with the minimul total costs of agents (accordingly, with the minimum costs of the Principal to stimulate the agents under optimal compensatory incentive functions). Next, construct an incentive scheme implementing this subset of actions. Finally, choose the result of activity with the most beneficial outcome for the Principal.

Now, let us give a formal description to the solution of the incentive problem in an OS with aggregation of information about agents' activity.

Define the set of agents' action vectors leading to a given result z of activity:

$$Y(z) = \{y \in A' | Q(y) = z\} \subseteq A', z \in A_0.$$

Recall that, under observable actions of agents, the minimum costs of the Principal to implement the action vector $y \in A'$ equal the total costs of agents $\sum_{i \in N} c_i(y)$. Similarly, we evaluate the minimum total costs of agents to achieve the result of activity $z \in A_0$: $\tilde{\vartheta}(z) = \min_{y \in Y(z)} \sum_{i \in N} c_i(y)$, and the corresponding action set $Y^*(z) = Arg \min_{y \in Y(z)} \sum_{i \in N} c_i(y)$, which attains the minimum.

Fix an arbitrary result of activity $x \in A_0$ and an arbitrary vector $y^*(x) \in Y^*(x) \subseteq Y(x)$. We make a technical assumption as follows: $\forall\ x \in A_0$, $\forall\ y' \in Y(x)$, $\forall\ i \in N$, $\forall\ y_i \in Proj_i\ Y(x)$: the function $c_j\ (y_i, y'_{-i})$ does not decrease in y_i, $j \in N$. It was demonstrated in Novikov and Tsvetkov (2001) that:

(1) under the incentive scheme

$$\sigma^*_{ix}(z) = \begin{cases} c_i(y^*(x)) + \delta_i, & z = x \\ 0, & z \neq x \end{cases}, i \in N, \tag{2.14}$$

the agents' action vector $y^*(x)$ is implementable as a unique equilibrium with the minimum costs of the Principal to stimulate agents (these costs constitute $\tilde{\vartheta}(x) + \delta$, $\delta = \sum_{i \in N} \delta_i$);

(2) the incentive scheme (2.14) enjoys δ-optimality.

Hence, Step 1 of solving the incentive problem (2.13) is to find the minimum incentive scheme (2.14) which (a) incurs the Principal's costs $\tilde{\vartheta}(x)$ to stimulate the agents and (b) implements the agents' action vector leading to the given result of activity $x \in A_0$. And Step 2 lies in evaluating the most beneficial (for the Principal) result of activity $x^* \in A_0$ via resolving the problem of optimal incentive-compatible planning:

$$x^* = \arg\max_{x \in A_0} [H(x) - \tilde{\vartheta}(x)]. \tag{2.15}$$

And so, the expressions (2.14) and (2.15) provide the solution to the problem of optimal incentive scheme design in the case of agents' joint activity.

Next, we explore how the Principal's ignorance (infeasibility of observations) of agents' actions affects the efficiency of incentives. By a natural assumption, the Principal's income function depends on the result of activity in the OS. Consider two possible cases, namely,

1. the actions of agents are observable, and the Principal motivates agents based on their actions and the result of collective activity;
2. the actions of agents are unobservable, and the incentives depend on the observed result of collective activity (exclusively).

The idea is to compare the efficiency of incentives in these cases.

Under observable actions of agents, the Principal's costs $\vartheta_1(y)$ to implement the agents' action vector $y \in A'$ constitute $\vartheta_1(y) = \sum_{i \in N} c_i(y)$, and the efficiency of incentives is $K_1 = \max_{y \in A'} \{H(Q(y)) - \vartheta_1(y)\}$ (see the previous section).

The actions of agents being unobserved, the minimum costs of the Principal $\vartheta_2(z)$ to implement the result of activity $z \in A_0$ are defined by (see (2.14) and (2.15)): $\vartheta_2(z) = \min_{y \in Y(z)} \sum_{i \in N} c_i(y)$. Accordingly, the efficiency of incentives makes up $K_2 = \max_{z \in A_0} \{H(z) - \vartheta_2(z)\}$.

The paper (Novikov and Tsvetkov 2001) argued that $K_1 = K_2$. The described phenomenon can be called the **principle of aggregation** or *the perfect aggregation theorem* for incentive models. Besides comparative efficiency estimation, the phenomenon has an extremely important methodological sense. It turns out that, under a collective incentive scheme, the Principal ensures the same level of efficiency as in the case of a corresponding individual incentive scheme!

In other words, aggregation of information by no means decreases the operational efficiency of an organizational system. This sounds somewhat paradoxically, since existing uncertainties and aggregation generally reduce the efficiency of managerial decisions. The model considered includes *perfect aggregation*. In practice, the practical interpretation is that the Principal does not care what actions are selected by the agents: they must lead to the desired result of activity under the minimum total costs. *The informational load* on the Principal goes down, yet the efficiency of incentives remains the same.

Therefore, the performed analysis yields the following conclusions. If the Principal's income depends only on the aggregated indicators of agents' activity, their usage is reasonable for agents' motivation. Even if the individual actions of agents are observed by the Principal, an incentive scheme based on these actions does not increase the efficiency of control (but definitely raises the informational load on the Principal).

Thus, the compensation principle (Novikov 2013a, c) is generalized to models with data aggregation in the following way. The minimum costs of the Principal to implement a given result of activity in an OS are defined as the minimum total costs of agents compensated by the Principal (provided that the former choose an action vector leading to this result of activity). This idea is also used in the models of team building and functioning below.

2.3 Incentives in Agents' Self-coordination

Above we have considered hierarchical two-level systems, where the upper level corresponds to a Principal and the lower level is occupied by controlled agents. Now, consider an organizational system composed of n agents located on a single hierarchical level. Our intention lies in analyzing the capabilities of their coordinated interaction within the game-theoretic model.

In the general case, the issue regarding the choice of agents with independent decision-making based on their individual interests remains open. If there exists a dominant strategy equilibrium (DSE), then researchers often believe that agents choose exactly dominant strategies (Novikov 2013c). A DSE being absent, a common approach is to consider a Nash equilibrium as the state of a system. Imagine that several Nash equilibria take place and some of them appear undominated by other equilibria in the Pareto sense. In such conditions, agents are assumed to choose undominated equilibria.

Concerning their practical interpretations, the concepts of dominant strategy equilibria and Nash equilibria reflect the individual rationality of agents' behavior. In the former case, there exists an optimal action independent from an opponents' action profile, whereas in the latter case a unilateral deviation of any agent becomes nonbeneficial to it if all other agents follow the equilibrium actions (Myerson 1991; Novikov 2013c).

Unfortunately, in many situations individual rationality contradicts collective rationality (formally described by the Pareto axiom, i.e., a hypothesis that the state of a system must be efficient). This conflict consists in the following. On the one hand, the set of individually rational actions (e.g., a DSE or Nash equilibrium) can be dominated by another set of actions (where all agents obtain not smaller payoffs and some agents gain strictly more). On the other hand, there may be several collectively rational (Pareto efficient) actions, and they can be unstable against the unilateral deviations of agents (there exists an agent who increases its payoff via an appropriate variation of the action). Furthermore, in cooperative games such behavior can be demonstrated by coalitions (groups of agents) and the solution of a game must enjoy stability against these deviations. Thus, the correlation of individual and collective rationality forms a key problem in game theory (see examples and references in Fudenberg and Tirole 1995; Germeier Yu 1986; Myerson 1991).

It seems intuitively clear that, if there is a best behavioral line for all agents (in comparison with individual rationality), one should design a penalty mechanism for those agents deviating from this line. Such "penalization" can be performed by agents or a meta-player (a Principal). Note that a penalty mechanism turns out "external" to agents and is often dictated, e.g., by a Principal, or represents the subject of their negotiation (an extension of the game Germeier Yu 1986). Let us clarify this statement.

Suppose that several plays of a game are organized successively. By varying their actions, agents can penalize an agent in the current or future periods for its deviation in the preceding period. Such strategies are constructed in theory of repetitive games (Fudenberg and Tirole 1995). The things seem more complicated in the static mode (a single-play game), as the threat of future penalization by partners becomes pointless.

However, the threat of penalization acquires a definite sense in the static mode if there is a third (external) subject with powers of authority, e.g., a Principal. By applying control actions, viz., stimulating agents, imposing penalties, etc., the Principal can make nonbeneficial their unilateral deviation from a collective optimum. In other words, the Principal guarantees the Nash stability of a Pareto optimal strategy. This is the first thing the Principal suggests to agents. The second effect from the Principal consists in reduced data processing by agents. Really, consider, e.g., Nash equilibrium "evaluation"; each agent must know the goal functions and admissible sets of all agents so that, again, each agent can independently solve the system of inequalities defining a Nash equilibrium. Now, assume that we incorporate the Principal into the system. Being aware of all relevant information on each agent (the mutual awareness of agents becomes unnecessary), the Principal easily calculates all equilibria, designs an incentive-compatible system of the so-called "side payments" (see the description of the incentive problem above) and provide the corresponding information to agents. The stated control problem can be solved by an agent (the initiator of interests' coordination), or agents simply choose their representative. An alternative is when agents invite a third party for interests' coordination (an analyst, a consulting company, etc.).

Consider the case without the explicit presence of a Principal and describe the corresponding problem of horizontal interests' coordination.

Fix a vector $x \in A'$ and study the following system of side payments:

$$\sigma_{ij}(x, y_j) = \begin{cases} s_{ij}(x), & y_j = x_j \\ 0, & y_j \neq x_j \end{cases}, i, j \in N. \tag{2.16}$$

Here $\sigma_{ij}(\cdot) \geq 0$ denotes the payment of agent i to agent j ($i, j \in N$). Naturally, $\forall\, x \in A'$: $s_{ii}(x) = 0$, i.e., an agent pays itself nothing, $i \in N$. Hence, the system of payments (2.16) is defined by $(n^2 - n)$ numbers.

Now, express the condition that x forms a Nash equilibrium in the agents' game:

$$\sum_{k \in N} s_{ki}(x) \geq \max_{y_i \in A_i} f_i(y_i, x_{-i}) - f_i(x), i \in N. \tag{2.17}$$

In this formula, we believe that any agent pays other agents regardless of its own action.

Note that our analysis ignores an important issue as follows. How can one force agents to pay each other under the assumption that an appropriate compulsion mechanism does exist? (otherwise, a certain agent may disagree to pay other agents after receipt of their payments). A possible compulsion mechanism is to introduce a Principal in the system–a higher-level representative in the hierarchy with the power of imposing penalties on agents refusing to fulfill their obligations. Such behavior (opportunistic behavior) is explored in contract theory (Hart and Holmstrom 1987; Laffont and Martimort 2001; Salanie 2005).

Suppose that there exists a vector $u = (u_1, u_2, \ldots, u_n)$ restricting agents' payoffs–the so-called *reserved utility*. The quantity u_i specifies the guaranteed payoff of agent i from participation in an organizational system, $i \in N$. Reserved utility can be evaluated from a Nash equilibrium in the absence of interests' coordination: $u_i = f_i(y^N)$, or as the guaranteed payoff $u_i = \max\limits_{y_i \in A_i} \min\limits_{y_{-i} \in A_{-i}} f_i(y_i, y_{-i})$, or by another method.

Then the individual rationality condition of agent i (the condition of its participation in the interests' coordination procedure) can be formulated as

$$f_i(x) + \sum_{k \in N} s_{ki}(x) - \sum_{j \in N} s_{ij}(x) \geq u_i, i \in N. \tag{2.18}$$

Therefore, agent's payoff in a new equilibrium must be not smaller than its reserved utility after the payments of all agents.

And finally, sum up inequalities (2.18) over all agents (in this case, "internal" payments get compensated) to arrive at the following result. **By side payments, one can pass to a system state, where the total payoff of all participants is not less than in the initial state**.

The set of incentive-compatible plans in this model comprises plans such that there exists a system of side payments (2.16) meeting the conditions (2.17) and (2.18):

$$S = \{x \in A' \mid \exists s_{ij}(x), i, j \in N : (2.17), (2.18)\}. \tag{2.19}$$

Consider an example. *Linear* organizational systems are the ones, where the goal function of each agent linearly depends on the strategies of all agents:

$$H_i(y) = a_{i0} + \sum_{j \in N} \alpha_{ij} y_j. \tag{2.20}$$

The quantities $\{\alpha_{ij}\}$ and $\{\alpha_{i0}\}$ are known constants and, without loss of generality, let $A_i = [0;\ 1]$, $i \in N$. In linear systems, each agent has the dominant strategy $y_i^D = \mathrm{Sign}(\alpha_{ii})$, where $\mathrm{Sign}(z) = \begin{cases} 1, & z \geq 0 \\ 0, & z < 0 \end{cases}$.

Denote $\beta_j = \sum_{i \in N} \alpha_{ij}$, $\beta_0 = \sum_{i \in N} \alpha_{i0}$. Then the total payoff of all agents makes up

$$\sum(y) = \beta_0 + \sum_{j \in N} \beta_j y_j. \tag{2.21}$$

The following action of agent i is Pareto optimal and maximizes the expression (2.21):

$$y_i^P = \mathrm{Sign}(\beta_i), i \in N. \tag{2.22}$$

If $\forall\, i \in N$: $\mathrm{Sign}(\alpha_{ii}) = \mathrm{Sign}(\beta_i)$, then the DSE enjoys Pareto efficiency. If $\exists\, i \in N$: $\mathrm{Sign}(\alpha_{ii}) \neq \mathrm{Sign}(\beta_i)$, then interests' coordination is required for agents.

We endeavor to establish conditions when the *plan* y^P becomes incentive-compatible, i.e., there exists a corresponding system of agents' mutual payments satisfying inequalities (2.17) and (2.18). For simplicity, set $n = 2$:

$$f_1(y) = y_1 - 2y_2, f_2(y) = -3y_1 + y_2.$$

The dominant strategy of each agent is choosing the unit action: $y^D = (1;\ 1)$. And the agents' payoffs constitute $f_1(y^D) = -1$, $f_2(y^D) = -2$.

The maximum sum of the goal functions is achieved under the action vector $y^P = (0;\ 0)$ which leads to the agents' payoffs $f_1(y^P) = f_2(y^P) = 0$.

Zero actions are beneficial to both agents (such choice dominates the DSE in the Pareto sense). However, this is not a Nash equilibrium, as any agent easily increases its own payoff by a nonzero action (simultaneously decreasing the opponents' payoff).

As reserved utility, choose the agent's payoff in the DSE: $u_i = f_i(y^D)$, $i = 1, 2$.

Then the system of inequalities (2.17) acquires the form

$$s_{12}\left(y^P\right) \geq 1, s_{21}\left(y^P\right) \geq 1;$$

and the system of inequalities 2.18) gets reduced to

$$s_{12}\left(y^P\right) - s_{21}\left(y^P\right) \geq -2, s_{21}\left(y^P\right) - s_{12}\left(y^P\right) \geq -1.$$

The sum of the mutual payments of agents is minimized under

$$s_{12}(y^P) = 1, s_{21}(y^P) = 1.$$

Interestingly, each agent pays the opponent exactly the amount received from it: in fact, payments are pointless, the only important thing is the agreement about the conditions of such payments!

On the one hand, the difference $\Sigma(y^P) - \Sigma(y^D) = 3$ can be treated as the effect owing to interests' coordination. On the other hand, this quantity estimates the maximum beneficial payments of agents to an external arbitrator (e.g., a Principal) so that it establishes and guarantees observance of game rules.

Consequently, **the necessity and feasibility of efficient interests' coordination among interacting agents explain hierarchies' occurrence in organizational systems.**

2.4 Problems of Agents' Preferences Identification

Motivation represents a key function of organizational control and consists in stimulating controlled subjects to choose actions desired by a Principal. Competent selection of an incentive scheme calls for predicting possible responses of subordinates to certain variations in the forms and amounts of wages. Accordingly, it is desired to know its preferences regarding these factors. Description of controlled subjects (*agents*) within motivation problems and incentive problems (Armstrong 2000; Novikov 2013c) lies, first, in defining their preferences regarding the forms and amounts of wages, viz., possible responses (variations in *labor supply*) to variations in an incentive scheme (Novikov 2010).

Rather complete (theoretical and experimental) investigations of labor demand and supply have been conducted mostly in countries with advanced market economy. According to the modern circumstances in Russia, the experience and data of domestic research seem insufficient, whereas unadapted usage of foreign experience appears unreasonable. On the other hand, the experimental studies of labor supply performed by foreign researchers *par excellance* proceed from analysis of actual data on incomes and working time acquired via polling (e.g., Panel Study of Income Dynamics). The average curve of labor supply is constructed using actual earned incomes gained by respondents and their actual working time. Applying such approach to Russian economy would yield a paradoxical result: labor supply (measured as the actual working time) is almost independent from wages (see the discussion in Myerson 1982). Furthermore, if we are interested in the motivational role of financial incentives (the influence on an agent depending on other primary characteristics such as sex, age, education level, etc.), then averaged indices may appreciably distort "the real picture." Notably, panel or other "averaged" statistical data make it impossible to explore the *individual strategies of labor supply* comprehended as the relationship between the desired working time of an individual and a wage system and its parameters (wage rates, etc.).

Taking into account the above grounds, the book (Novikov 2010) focused on individual questioning: a respondent models its behavior in different conditions and fills an electronic questionnaire. This approach seems advantageous, as it allows drawing the labor supply curve averaged over actual data (including comparison with the results of other types of questioning) and examining[4] the relationship between individual preferences and the forms and amounts of wage. That is, the approach enables analyzing the relationship between the individual strategies of labor supply and the individual characteristics of respondents.

Suppose that the strategy of an agent as the labor supply side is the choice of working time under a given wage and working conditions. For simplicity, we believe that the only alternative to working time is leisure time.[5] Hence, labor supply appears equivalent to leisure demand (Ashenfelter and Layard 1986; Mas-Colell et al. 1995). In addition, assume that the maximum admissible working time in a day makes up $T = 16$ h (at least, 8 h must be allocated to sleeping, eating, etc.), i.e., *working time* $\tau \in [0; 16]$. If t designates *free time* (leisure activities), then $\tau + t = T$. Again, for the sake of simplified exposition, we hypothesize that the total income is proportional to working time (if there is no clear provision for the opposite). This means that labor market admits only proportional incentive schemes (time wages) with fixed wage rates independent from the total working time and other sources of income are absent. All results can be generalized to the case of arbitrary wage systems, see (Novikov 2013c) for details.

Under the stated assumptions, the alternative costs of 1-h leisure equal the wage rate (and vice versa)–the extra earnings owing to working within this period of time. Let us analyze agent's behavior on labor market, i.e., its preferences in the "labor-leisure" dilemma. Here labor supply is characterized by agent's desired working time.

According to labor economics, individual labor supply is defined by the income effect and the substitution effect (Ashenfelter and Layard 1986; Mas-Colell et al. 1995).

The income effect gets manifested in the following. For a fixed *wage rate* α (wage per unit time), the desired working time goes down as the total income grows. Imagine that an agent aims at maintaining a certain level of the total income. Then the income effect reduces the desired working time in case of increasing the wage rate. And conversely, for maintaining a fixed level of the total income, an agent has to raise working time under a reduced wage rate.

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[4] No doubt, it may happen that the answers of respondents mismatch the reality: in real-life conditions, respondents can choose other actions than they report during questioning. A separate issue concerns the truthfulness of their answers. Being active, respondents can demonstrate strategic behavior and manipulate information. For instance, if agents know that managerial decisions affecting their interests will be made based on their answers, they can report untrue information to guarantee most beneficial decisions. Analysis of deliberate and purposeful manipulation of procedures makes the subject of separate (perhaps, extremely promising) research, but goes beyond the scope of this work.

[5] This simplifying assumption eliminates from further consideration the problems of agent's decision-making on hiring, firing, job hopping and hunting, etc. Moreover, in most real situations an employee is unable to choose working time independently or selects it from a short range.

The substitution effect leads to the following. Wage rate growth increases the desired working time τ, i.e., the alternative costs of 1-h leisure go up and an agent prefers working more time.

Thus, under the income effect, an agent responds to wage rate growth by reducing labor supply; domination of the substitution effect brings to labor supply increase.

Suppose that the preferences of a given agent on the set of admissible incomes and working time (or leisure time) are described by its *utility function* $u(q, t)$. Here q denotes the total (e.g., daily, monthly, etc.) *income*, and $t \in [0; T]$ specifies leisure time.

Further exposition focuses on the case of a fixed wage rate. If unearned incomes are absent, working time τ yields the wage $q(\alpha) = \alpha\ \tau(\alpha)$ to the agent.

Assume that agent's preferences are defined as follows. First, the agent has the right to choose any daily working time under a fixed time wage. Second, we know the relationship between the desired working time τ and the wage rate α. Which decision rule is adopted by the agent in such choice conditions? Agent's decision-making principle (reflected by the function τ(α)) will be called its *strategy*.

The list of possible strategies includes income maximization, free time maximization, ensuring daily working time above a certain threshold, and so on (Novikov 2010). Consider the following hypothetical example illustrated by Fig. 2.1.

On the plane (α, τ(α)), draw the isoquant curves corresponding to the total income $q_1 \leq q_2 \leq q_3 \leq q_4$. These values can be interpreted as the subjective norms of total income. For instance, the minimum income value q_1 means the living wage, q_2 is the average income of a social group this agent belongs to, q_3 gives the total income desired by the agent at the current moment under existing external conditions, q_4 indicates the total desired income unachievable under existing external conditions (as it corresponds to a higher level of welfare), and so on.

In Fig. 2.1, individual strategies are marked by heavy line. Let us analyze the characteristic segments of wage rate values. Within the segment $[0; \alpha_1]$, all available time is dedicated to working, but this yields a smaller income than q_1. The free time maximization strategy dominates on the segment $[\alpha_1; \alpha_2]$ under a constant

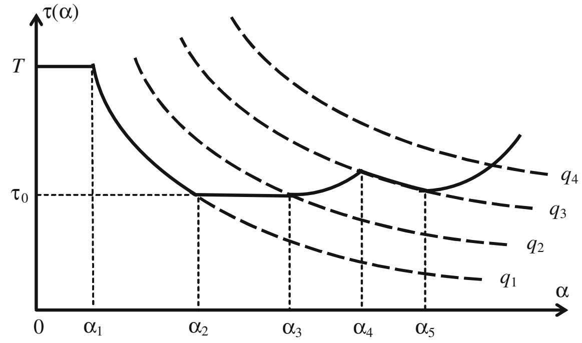

Fig. 2.1 A combination of individual strategies

income q_1 (the income effect takes place). The segment [α_2; α_3] is remarkable for additional "activation" of the strategy "working not less than τ_0 h daily." Having reached the income level q_2, the agent strives for increasing the total income to the new "norm" q_3 following wage rate growth. In other words, the curve goes up on the segment [α_3; α_4] (the substitution effect), and within the segment [α_4; α_5] the agent is quite satisfied with its new total income (the curve moves along the isoquant curve q_3). As wage rate exceeds α_5, the agent observes the feasibility of achieving a higher level of welfare (the curve again demonstrates growth, which answers the substitution effect). Interestingly, the curve in Fig. 2.1 meets *the income monotonicity condition* (Novikov 2010): as wage rate raises, the agent prefers working time such that its total income is not decreasing.

The book (Novikov 2010) described the results of verification experiments for the hypothesis on the existence of the following agents' typology. According to the hypothesis, the types of labor supply agents depend on their response to wage rate variations. The experiment yielded 5541 correctly filled questionnaires. The author acquired information corresponding to the following indicators:

- *primary social indicators*: sex, age, family status, family structure (the number of co-residing dependents–children and pensioners), education level, current learning (type of educational institution), position at the principal place of business;
- *primary economic indicators*: the actual total income of a person at the principal place of business, the actual daily mean working time at the principal place of business, the actual average per capita income of a family (taking into account all working members), the minimum monthly wage for which a respondent is willing to work daily for a given time (from 1 to 16 h), the desired daily working time under a given wage rate within a defined range.

Different individual labor supply strategies lead to certain relationships between the desired working time τ and the wage rate α. Experimental data testify to an important feature: by analyzing the real curves $\tau(\alpha)$ and performing expertise (!), one can identify five qualitatively different types of agents (the corresponding actual data illustrating this thesis are provided below):

- *type 1* the desired working time is independent or almost independent from the wage rate starting from some threshold α^0 (an agent disagrees to work under smaller wage rates), see Fig. 2.2;
- *type 2* the desired working time increases monotonically with the wage rate exceeding the "minimum" threshold α^0, see Fig. 2.3;
- *type 3* the desired working time monotonically decreases with the wage rate exceeding the "minimum" threshold α^0, see Fig. 2.4;
- *type 4* the desired working time increases with the wage rate exceeding the "minimum" threshold α^0, and decreases for $\alpha \geq \alpha_{max}$, see Fig. 2.5;
- *type 5* the desired working time has nontrivial behavior with wage rate variation (e.g., possesses a minimum or even several minima, etc.), see Fig. 2.6.

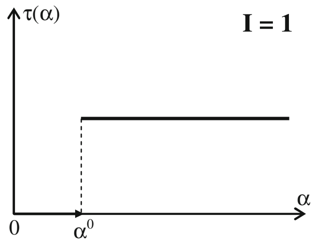

Fig. 2.2 Type 1 of agents

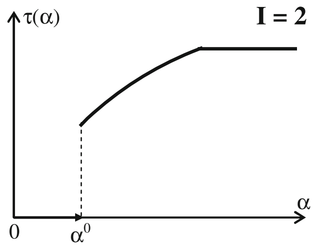

Fig. 2.3 Type 2 of agents

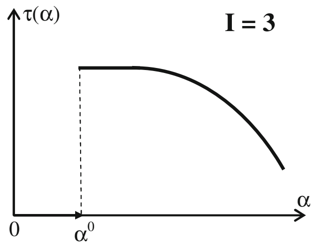

Fig. 2.4 Type 3 of agents

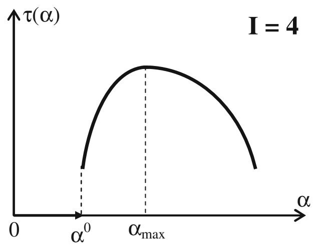

Fig. 2.5 Type 4 of agents

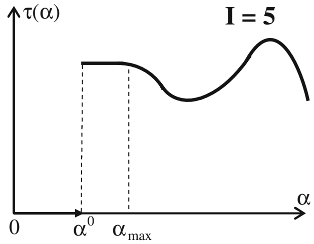

Fig. 2.6 Type 5 of agents

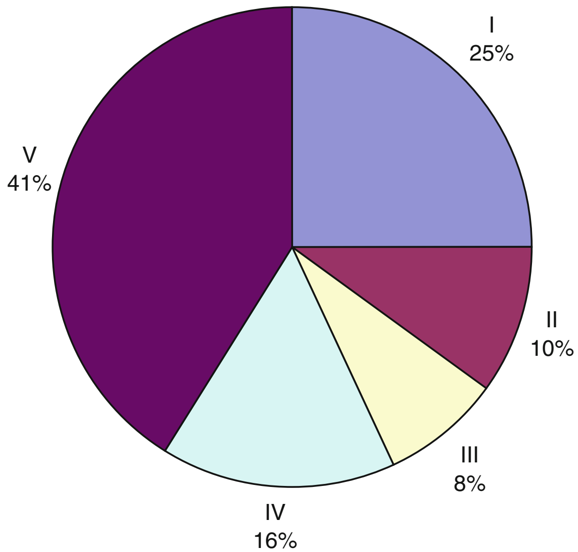

Fig. 2.7 The distribution of respondents by their types (I)

The results of this expert classification fully agree with the results of automatic classification of labor supply curves obtained in Novikov (2010).

The corresponding indicator *I* which reflects agent's type (predetermines its individual labor supply strategy) and takes values {1; 2; 3; 4; 5} is called **the type of individual labor supply strategies** or simply *agent's type*.

The suggested typology of agents was tested (Novikov 2010) using the results of a similar questioning of more than 400 respondents in 1999. Almost the same sample size was selected for the study performed in 2003. Recall that in 2009 the sample size exceeded 5000 respondents. The time-invariable distribution of respondents by their types is demonstrated in Fig. 2.7.

Therefore, **the existence of five different "type" values allows claiming the presence of five general types of agents, which are defined by common classes of their individual labor supply strategies**. The experimentally established five types of agents can be described from the viewpoint of individual labor supply strategies introduced in Novikov (2010) based on a series of hypotheses. Moreover, the book (Novikov 2010) posed and solved the problem of finding statistically significant relationships between the primary characteristics of agents and the types of their individual labor supply strategies.

It is possible to explain the existence of the five types of individual labor supply strategies in different ways. By proceeding from agent's decision-making criteria (income maximization and free time maximization), we obtain that type 1 corresponds to the following situation. An agent works a common fixed time without income/free time maximization. Next, type 2 is when income maximization dominates free time maximization, type 3 describes the opposite case. If an agent makes decisions based on both criteria equally, we observe type 4 or type 5. Choosing other grounds for agent's decision-making or accepting some typology of its personal qualities, one can suggest other interpretations for the types of individual behavior strategies.

In conclusion, we discuss how the results of such experiments may serve for identification of the above game-theoretic incentive models.

The knowledge of the relationship $\tau(\alpha)$ allows constructing the functions $\alpha(\tau)$, $q(\alpha) = \alpha\ \tau(\alpha)$ and $q(\tau) = \tau\ \alpha(\tau)$. Imagine that the agent's action is the choice of the working time $y = \tau$ (in this case, the incentive $\sigma(\tau)$ and the Principal's income $H(\tau)$ both depend only on its working time). Then it is necessary to evaluate the optimal working time from the Principal's viewpoint: $\tau^* = \arg \max_{\tau \in [0;T]} \{H(\tau) - q(\tau)\}$. If agent's working time has a more complicated dependence on its action, e.g., $y = G(\tau)$ (but the Principal and an operations' researcher know it), then the minimum stimulation costs of implementing the action y make up $\upsilon(y) = \min_{\tau \in \{\tau \geq 0 \mid G(\tau) = y\}} q(\tau)$. The optimal implementable action y^* is the action maximizing the Principal's goal function, i.e., the difference between the Principal's income function $H(y)$ and the minimum stimulation costs: $y^* = \arg \max_{y \in A} \{H(y) - \upsilon(y)\}$.

Recall that the game-theoretic framework characterizes agent's preferences (see above) by its goal function $f(\cdot)$, i.e., the difference between its incentive and costs: $f(y, \sigma) = \sigma(y) - c(y)$, where $y \in A$ denotes agent's action. In macroeconomic models, agent's preferences are specified by a utility function $u(q, t)$ defined on the "income × free time" set or by the relationships $\tau(\alpha)$ (the desired working time τ as a function of the wage rate α) or $\alpha(\tau)$ (the minimum wage rate as a function of the working time).

We have emphasized that the variables of the utility function and the goal function possess a simple interconnection: $y \leftrightarrow \tau$, $\tau = T - t$, $\sigma \leftrightarrow q$, $A \leftrightarrow [0; T]$. Under the proportional incentive scheme, we have $q(\tau) = \alpha\ \tau$ (in the general case, $q(\tau) = \sigma(\tau)$).

Establishing interconnections between different models implies exploring the following problem. Information on the individual preferences is specified in one of the four ways (see Novikov 2010 and references therein):

I. We know the utility function $u(q, t)$;
II. We know the minimum time wage rate $\alpha(\tau)$ for which an agent agrees to work τ h;
III. We know the relationship $\tau(\alpha)$ between the desired daily working time τ and the time wage rate α;
IV. We know the goal function $f(\tau, \sigma)$.

For each of the four descriptions (under a given relationship), is it possible to "restore" other relationships and how should this be done? As a matter of fact, solution of this problem was introduced in Novikov (2010).

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