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Essays on private information: moral hazard, selection and capital structure

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ESSAYS ON PRIVATE INFORMATION: MORAL HAZARD, SELECTION AND CAPITAL STRUCTURE

by

Olena Chyruk

An Abstract

Of a thesis submitted in partial fulfillment of the
requirements for the Doctor of Philosophy
degree in Economics
in the Graduate College of
The University of Iowa

July 2009

Thesis Supervisor: Professor B. Ravikumar

ABSTRACT

This dissertation explores the implications of private information on the trade-off between incentives to work and risk-sharing, and on the choice of capital structure and performance of entrepreneurial firms. In Chapter 1 we characterize optimal dynamic contracts in environments with limited commitment and moral hazard. We study the implications of such contracts for the evolution of consumption and effort of the two agents who participate in an infinitely repeated risk-sharing arrangement. In these environments, we show the extent to which moral hazard restricts risk-sharing allocations prescribed in a limited enforceability environment. To put it differently, we investigate how the need to sustain a risk-sharing relationship in the presence of limited commitment restricts the punishments and rewards associated with optimal effort provision. We find that optimal contracts preserve some limited commitment properties even when there is private information. We also find that the steady state distribution of consumption is not degenerate. The need to provide incentives for work increases the variability of consumption near the bounds.

In Chapter 2, which is a joint work with Dzmitry Asinski, we contribute to the growing empirical literature focusing on the effects of capital structure on the performance of small business start-ups in their first years of existence. In contrast to most of the existing studies, we explicitly recognize potential endogeneity of the capital structure. Business financing is a choice that can be affected by unobservables and can also affect performance. This can lead to biased and inconsistent estimates. Our econometric specification allows joint modeling of capital structure and performance of business start-ups. We use a unique data set collected by the National Federation of Independent Business (NFIB) Foundation. Our results demonstrate that controlling for endogeneity of capital structure leads to qualitatively different results compared to a simple model assuming exogeneity. We find that outside equity has a negative effect on survival probability but positive effect on growth. Debt has a positive effect only on some measures of performance but not others.

Abstract Approved: ______________________________
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Graduate College
The University of Iowa
Iowa City, Iowa

CERTIFICATE OF APPROVAL

PH.D. THESIS

This is to certify that the Ph.D. thesis of

Olena Chyruk

has been approved by the Examining Committee for the thesis requirement for the Doctor of Philosophy degree in Economics at the July 2009 graduation.

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To my family

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ABSTRACT

This dissertation explores the implications of private information on the trade-off between incentives to work and risk-sharing, and on the choice of capital structure and performance of entrepreneurial firms. In Chapter 1 we characterize optimal dynamic contracts in environments with limited commitment and moral hazard. We study the implications of such contracts for the evolution of consumption and effort of the two agents who participate in an infinitely repeated risk-sharing arrangement. In these environments, we show the extent to which moral hazard restricts risk-sharing allocations prescribed in a limited enforceability environment. To put it differently, we investigate how the need to sustain a risk-sharing relationship in the presence of limited commitment restricts the punishments and rewards associated with optimal effort provision. We find that optimal contracts preserve some limited commitment properties even when there is private information. We also find that the steady state distribution of consumption is not degenerate. The need to provide incentives for work increases the variability of consumption near the bounds.

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CHAPTER 1
CONTRACTS UNDER MORAL HAZARD AND LIMITED COMMITMENT

1.1 Introduction

In this paper we characterize optimal dynamic contracts in environments with limited commitment and moral hazard. We study the implications of such contracts for the evolution of consumption and effort of the two agents who participate in an infinitely repeated risk-sharing arrangement. Here we construct several models in which two agents exert effort to produce output according to some stochastic production function. The models differ in the information available to the agents and enforceability of contracts. In particular, individual efforts may be private information, and contracts are not perfectly enforceable.

To this end, we propose the following models. There are two identical agents with access to the same stochastic production technology that converts effort into consumption goods. The agents are risk-averse and would like to smooth consumption streams across states and time. They start a contractual relationship in period zero and share combined outputs according to some optimal rules. We consider several possible environments.

The first two environments exhibit imperfect enforceability of contracts, but both agents have full information about the environment. Namely, the first model requires that the optimal contract has to be enforceable in any state of the world *before* the agents observe their output realizations. This implies that each agent can commit only to the contract that provides a consumption stream that is at least as good as the one he or she can get in autarky from tomorrow on. This is the type of commitment that is studied in Zhao (2007) in the model of double moral hazard. We call this model "ex-ante limited commitment model." The second type of commitment constrains optimal contracts to be enforceable in each state of the world *after* the agents observe their output realizations. We call this model "ex-post limited commitment model." Kocherlakota (1996) introduces this environment and shows that in some states of the world, the perfect risk-sharing is achieved: The ratio of marginal utilities of both agents stays the same as in the previous state or period for some output realizations. The difference between this model and Kocherlakota's is that the agents in our model employ production technology to generate income, while in his model, the income is an endowment process. In the ex-post commitment problem, the lower limit on the agent's lifetime utility varies with the current output, while in the ex-ante type it is constant across output states.

Our two final models introduce private information about efforts in the previous two models. That is, the third model includes private information about efforts and the ex-ante commitment problem, while the fourth model incorporates private information and the ex-post commitment problem. Both of these environments provide a look at how moral hazard restricts the risk-sharing allocations prescribed in a limited enforceability environment. To put it differently, we study how the need to sustain the risk-sharing relationship in the presence of limited commitment restricts the punishments and rewards needed to provide effort incentives in the presence of private information. The optimal contracts in these environments are compared to the ones in limited commitment environments with full information about efforts.

The presence of hidden actions complicates theoretical analysis, since the value function may fail to be concave on some parts of the domain. Here we take a different approach. To deal with the possibility of non-concavity, we follow Phelan and Townsend (1991), Sleet and Yeltekin (2001), and Prescott (1999) and convexify our models using lotteries. We use value function iterations and linear programming to solve the models and characterize optimal contracts using policy and value functions. In line with the literature on hidden actions and limited commitment, we also investigate the long-run behavior of contracts by simulating histories of optimal consumption and effort and determining the steady state dynamics of consumption and effort levels.

In this study, we find that the optimal contracts preserve some limited commitment properties even when there is private information about effort, and incentive provision is crucial. The consumption does not vary across states as much as in a simple double moral hazard when there are bounds on lifetime utilities. Unless one of the agents is close to his or her lower or higher bound, the aggregate consumption is split in half independently of output realizations and even in the presence of private information. If the agents are near the commitment bounds, then the one closer to the lower bound has to share his or her output with the other agent regardless of output realizations. This is due to the other agent's utility promise hitting the upper bound with no scope for an increase in future utility promises. In order to guarantee such a high utility promise to that agent, the contract increases his or her consumption in the current period. The agent near the lower bound is promised higher consumption in the future instead. In contrast, the standard principal-agent model predicts that consumption and utility promises should vary with output realizations, and higher output realizations should always be rewarded with higher current and future consumption.

We find that in the long run, the contracts in such limited commitment environments with and without private information do not exhibit "immiserization" property, with one agent consuming all the output and the other agent consuming nothing. In addition, we do not observe one of the agents being driven to lower bounds in the long-run. Rather, in the steady-state, the utility promises cluster around some middle value of utility promises for both agents, and the consumption distribution is clustered around the consumption levels that reflect the equal division of aggregate output.

Comparing limited commitment environments with full and private information, we show that the recommended work patterns significantly differ between them. When the efforts are observable, there is no need to motivate the agents to work through punishments and rewards of future consumption. As a result, the steady state distribution of utility promises is degenerate and only one of the agents exerts high effort in the steady state. In our models, the mass of the distribution is concentrated on some inside value of the utility promise space, and not on the lower bounds (with one agent consuming everything in the long run).

In the limited commitment environments with private information, the optimal contract has to provide incentives for effort. This leads to a less degenerate steady-state distribution of utility promises. The distribution is clustered around several states inside the bounds. In fact, we find that the expected steady state utility promises of the agents become closer in value under private information. This implies that in the world in which each agent is treated the same, the introduction of private information (and a need to provide incentives for work) leads to a "fairer" society in which both agents are almost equally likely to exert high effort.

To summarize, we show that when there is private information about efforts, the risk-sharing is diminished as optimal consumption has to vary more across states when the agents are constrained. The commitment bounds restrict the rewards and punishments rendering them ineffective near the limits. On the other hand, the presence of private information creates the society of working middle class, as the steady state distributions of utility promises and efforts are more equal.

We proceed as follows. In Section 1.2 we relate our research to existing literature. In Section 1.3 we describe our economic environments and introduce the limited commitment problems. In Section 1.4 we describe the restrictions imposed by private information in the models of limited commitment. In Section 1.5 we provide the recursive formulation. In Section 1.6 we give the parameterization of the models. In Sections 1.7 and 1.8 we summarize our results, and Section 1.9 concludes with research suggestions.

1.2 Related Literature

Mutual insurance arrangements were long considered in economic literature. The research has been motivated by empirical evidence that household consumption allocations do not reflect Pareto-efficient full risk-sharing outcomes that are predicted by the full information model with complete markets. In particular, empirical findings suggest that individual consumption is correlated with individual income. However, the basic model of complete markets predicts full insurance against idiosyncratic income shocks for the agents in the economy.

Several models explain this deviation from complete insurance by the presence of private information about individual income, effort, or preferences. For example, Green (1987), Thomas and Worrall (1990), Phelan and Townsend (1991), Atkeson and Lucas (1992), and Atkeson and Lucas (1995) find that incomplete risk-sharing is an efficient response to the problem of costly monitoring of unobservable variables. In addition, the properties of the agents may be perfectly observable to all agents, but it is costly for the third party to enforce the contracts between the agents because it cannot verify the agent-specific characteristics. To illustrate the implications of limited enforcement of contracts, Kocherlakota (1996) proposes a model in which contracts are enforceable only when they provide at least some specified level of lifetime utility. He finds that in such an environment, incomplete risk-sharing is an optimal response to this friction.

Kocherlakota (1996) and Zhao (2007) are the two papers that are most related to our paper. However, there several differences between these papers and ours.

Zhao (2007) is a theoretical paper that concentrates on contracts in a double moral hazard model. He also introduces limited commitment in his model and studies the implications of "ex-ante" commitment as described above. He does not, however, explore the role of such commitment constraints numerically. The version of his model is only one among our four models, and we explore it numerically in greater detail. We borrow our definition of "ex-post" commitment from Kocherlakota (1996). In his environment there is full information about the agents' characteristics, there is no production, and the agents receive stochastic endowment each period. We also investigate this type of environment in our model, and compare the allocations and histories with other models that have additional features, like unobservable actions.

The absence of "immiserization" effect in our private information models is similar to the findings of Atkeson and Lucas (1995). In our models, as well as in Atkeson and Lucas (1995), the lower and upper bounds are "reflecting barriers." It is enough to receive one high (low) output realization on the lower (upper) bound to be pushed back inside the bounds. In fact, the policy functions for future utility promises in our models resemble those in Atkeson and Lucas (1995), and that is why we get similar results.

The settings of our models allow us to compare some of our results to the results in the literature on relative contracts. Yeltekin (1997) considers the model with one principal and two agents who participate in separate production processes, but experience the same correlated productivity shock. The shock provides additional information on the output outcomes and is utilized in the optimal contract. The author finds that if both agents have the same output realizations, then the optimal contract prescribes the same level of consumption to both agents. When the outputs differ across agents, then the agent with the highest output is rewarded and the other one is punished with lower consumption. This does not happen in our environment. When none of the agents are constrained, they split the sum of either high or low outputs equally. However, if one of the agents is constrained then she has to be motivated to stay in a contract by being given a higher consumption. To put it differently, the other agent is promised a utility promise close to his upper bound, and in order to fulfill such a promise, more consumption has to be given to that agent. This decreases the consumption of the first agent. We also find that if one of the agents does better but is not constrained, then they split the aggregate output in half. In that sense, some of our models exhibit complete risk insurance in some states. The utility promises do vary in order to motivate the agent to work, and the agent who gets a higher output is rewarded for low values of current utilities, but receives relatively low future utility promise for relatively higher current utility promises.

In terms of computational approach, our paper is most closely related to Phelan and Townsend (1991) and Sleet and Yeltekin (2001) who introduce lotteries into a standard principal-agent model. We also follow dynamic contract literature and use utility promises as state variables that keep track of performance histories, which were introduced by Spear and Srivastava (1987).

1.3 The Limited Commitment Economy

In Sections 1.3.1-1.3.3 we consider the two models of limited commitment in which the effort levels are publicly observed. In particular, we consider two types of commitment problems. Section 1.3.2 presents the model with "ex-ante limited commitment." The optimal contract has to be enforceable in any state of the world *before* the agents observe their output realizations. This is the type of commitment that is studied in Zhao (2007) in a model of double moral hazard. The second type of commitment is of more interest to us, and it constrains optimal contracts to be enforceable in each state of the world *after* the agents observe their output realizations. We call this model the "ex-post limited commitment" model. Section 1.3.3 provides the description of this model. In Section 1.4 we consider the environments with these types of commitment, but in which the exerted efforts are private information. The presence of private information imposes additional restrictions on optimal contracts in the form of incentive-compatibility constraints.

1.3.1 Physical Environment

We consider the following discretized economy. Time is discrete and $t = 1, 2 ... \infty$. There are two infinitely lived risk-averse agents, indexed by $k = 1, 2$. They are identical in all respects. Both agents participate in output production individually and can enter into a mutual risk-sharing arrangement. If they enter into such an arrangement, then they have to respect the social contract. Otherwise, the agents will be forced into autarky and restricted to consume their own output. The risk-averse agents value risk-sharing because this allows them to smooth consumption across time and states. We assume that the technology is stochastic and converts the agent's effort into different realizations of output.

The timing of the model is as follows. In the beginning of a period t, provided the agents are in a contract, the contract recommends the actions to the agents. Then the agents decide whether to take the recommended action. Later they take their actions, and then their respective outputs are realized, which they share according to certain rules prescribed by the contract.

Formally, in period t the agent k chooses an effort level $a_t^k \in A = \{a_i\}_{i=1}^{na}$, where $a_{i+1} > a_i$ for all i, and receives a stochastic output in terms of consumption goods $q_t^k \in Q = \{q_i\}_{i=1}^{nq}$, where $0 < q_1 < q_2 < ... < q_{nq}$. Since this is a closed economy, the outputs of the two agents in period t, (q_t^1, q_t^2) determine the aggregate output available for consumption $q_t^1 + q_t^2 \in Q \times Q$. We assume that there is no technology for self-insurance available to the agents. Let $C = \{c_i\}_{i=1}^{nc}$ be a finite ordered set of consumptions of agent 1, with c_1 and c_{nc} being the minimal and maximal elements of the set C, respectively. Then the consumption of agent 1 in period t is given by $c_t^1 \in C$ and the consumption of agent 2 is given by $c_t^2 = q_t^1 + q_t^2 - c_t^1$.

We assume that the effort-contingent technology $P(q \mid a)$ is described by a stochastic matrix P with dimensions $na \times nq$. Then the production takes place according to the probability P_{ij}, where i identifies the exerted effort a_i and j identifies the output realization q_j. The matrix P satisfies monotonicity in a sense that the i-th row distribution stochastically dominates the one in the j-th row.

The social planner provides the agents with lotteries over infinite histories of effort, consumption, and output realizations.[1] Define $\Omega \equiv A \times A \times Q \times Q \times C = A^2 \times Q^2 \times C$ and let $\omega^t \in \Omega$ denote a $t-$period history. Define $\Pi(\Omega^\infty)$ to be the set of probability distributions over $\Omega^\infty \equiv \Omega \times \Omega \times ....$ These lotteries are denoted $\pi^\infty \in \Pi(\Omega^\infty)$. The agents maximize ex-ante expected lifetime utilities and discount the future by a common discount factor $\beta \in (0,1)$. The agent k evaluates the lotteries over the streams of consumption according to her preferences given by the utility function:

$$U^k(\pi^\infty) = E_{\pi^\infty} \sum_{t=0}^{\infty} \beta^t \left[u(c_t^k) - g(a_t^k) \right]. \tag{1.1}$$

The instantaneous utility function $u : C \rightarrow \Re$ is increasing and strictly concave. To guarantee an interior solution we assume that $\lim_{c \rightarrow 0} u'(c) = +\infty$. The disutility function $g : A \rightarrow \Re$ is increasing and concave in effort a. The expectation E_{π^∞} denotes the expectation under the probability measure π^∞.

Let agent 2 be the principal and agent 1 be the agent. Then any optimal contract has to deliver some initial lifetime utility promise w_0 to agent 1. That is, for a given initial lifetime utility promise w_0 the contract maximizes the lifetime utility (1.1) of agent 2 subject to guaranteeing at least w_0 to agent 1. This constraint is called the participation constraint and it requires that the optimal contract $\pi^\infty \in \Pi(\Omega^\infty)$

[1]This approach is similar to the one used in Phelan and Townsend (1991) in a standard principal-agent model. In contrast, in our environment both the principal and the agent are risk-averse and they both participate in individual production.

satisfies:

$$w_0 = E_{\pi^\infty} \sum_{t=0}^{\infty} \beta^t \left[u(c_t^1) - g(a_t^1) \right]. \tag{1.2}$$

With a slight abuse of notation, we denote the contract π^∞ that satisfies the participation constraint (1.2) by π^{∞,w_0}.

Since the contract π^{∞,w_0} implies probabilities of output realizations conditional on actions, but it is also a choice variable, we need to impose some additional restrictions on the contract to ensure that the optimal contract is consistent with the exogenous stochastic technology $P(q \mid a)$. For all $\omega^t \in \Omega^t$, $q_t^1, q_t^2 \in Q$, and $a_t^1, a_t^2 \in A$ we require that:

$$\sum_{\omega^{t-1} \times a_t^1 \times a_t^2 \times q_t^1 \times q_t^2 \times C} \pi^{\infty,w_0}(\omega^t) = \sum_{\omega^{t-1} \times a_t^1 \times a_t^2 \times Q \times Q \times C} P(q_t^1 \mid a_t^1) P(q_t^2 \mid a_t^2) \pi^{\infty,w_0}(\omega^t). \tag{1.3}$$

We also require that π^∞ is a valid probability measure:

$$\sum_{A^2 \times Q^2 \times C} \pi^{\infty,w_0}(\omega^t) = 1, \tag{1.4}$$

and

$$\pi^{\infty,w_0}(\omega^t) \geq 0, \tag{1.5}$$

for all $(a^1, a^2, q^1, q^2, c) \in \Omega^\infty$.

When there are no commitment problems, the lowest lifetime utility the agent can get is when she consumes the smallest possible consumption $\underline{c} = c_1$ and exerts the smallest possible effort $\underline{a} = a_1$ (because the agent cannot be forced to exert high effort) with certainty forever, or $\underline{w} = [u(\underline{c}) - g(\underline{a})]/(1-\beta)$. The highest lifetime utility is given by $\overline{w} = [u(\overline{c}) - g(\underline{a})]/(1-\beta)$, when the agent gets the highest consumption possible $\overline{c} = c_{nc}$ and exerts the smallest effort $\underline{a} = a_1$ with certainty. However, we are interested in a model in which the agents have an incentive to break the contract, and therefore, we require the optimal contract to be self-enforcing. The lower and upper bounds defined above may never be achievable if the autarky environment gives higher lifetime utility.

1.3.2 The Ex-Ante Commitment Problem

This Section introduces the ex-ante limited commitment contract, while Section 1.3.3 describes the ex-post limited commitment contract.

The limited commitment constraints require that the agents' lifetime utilities are greater than some lower bounds that represent their outside options. Otherwise, the agent can take his or her outside option and leave the contract. In our ex-ante limited commitment model, such a natural lower bound is the lifetime utility that the agent can get if she does not participate in a risk-sharing contract and lives in autarky consuming her output. After effort is chosen in period t, *before* the output is realized, agent k can guarantee himself the expected value associated with consuming his own income stream and exerting optimal level of effort from time t onward. This value is given by

$$U_{aut}(a) = \max_{\{a_{t+\tau}\}_{\tau=0}^{\infty}} E_t \sum_{\tau=0}^{\infty} \beta^{\tau} \left[u(q_{t+\tau}^k) - g(a_{t+\tau}^k) \right]. \tag{1.6}$$

The expectation is taken with respect to the stochastic production technology. The value of autarky is the same for both agents as the agents are identical. This maximization problem (1.6) is well defined and does not require the use of lotteries to be solved. Note that the autarkic effort levels in general will be different from the effort levels chosen in the social planner's problem. Also, in order to make our investigation nontrivial, we assume that there are other possible allocations besides the autarkic allocation, defined as $c^k_{aut} = \{q^k_t\}^{\infty}_{t=1}$ and $a^k_{aut} = \{a^k_t\}^{\infty}_{t=1}$ for $k = 1, 2$, and give more utility to both agents. This assumption is not restrictive as we can always find a set of parameters for which the above is true. The definition of ex-ante limited commitment is as follows.

Definition 1.1. A contract π^{∞} is the ex-ante limited commitment contract if

$$E_{\pi^{\infty},w_0} \sum_{\tau=0}^{\infty} \beta^{\tau} \left[u(c^k_{t+\tau}) - g(a^k_{t+\tau}) \right] \geq U_{aut} \tag{1.7}$$

holds in every period $t = 1, ...\infty$ for $k = 1, 2$.

The inequality (1.7) implies that the optimal allocation of consumption and effort provides the value to the agent that is at least as high as the lifetime value of autarky. This constraint is the same in every period and the lower bound U_{aut} does not fluctuate with income realization.

1.3.3 The Ex-Post Commitment Problem

Now we introduce the constraints associated with ex-post limited commitment. This definition follows Kocherlakota (1996). It requires that in every period, the optimal contract assigns positive probability to such a stream of consumption and efforts that the value of this stream is at least as high as the value of reverting into autarky this period and staying in autarky forever. That is, *after* the output is realized in period t, the optimal current consumption and future consumption and effort stream have to deliver at least as much utility to the agent as the consumption of his or her current output and future consumption and effort stream in autarky do. The formal definition of the ex-post commitment problem is given below.

Definition 1.2. A contract π^{∞,w_0} is the ex-post limited commitment contract if

$$u(c_t^k) + E_{\pi^{\infty,w_0}} \sum_{\tau=1}^{\infty} \beta^{\tau} \left[u(c_{t+\tau}^k) - g(a_{t+\tau}^k) \right] \geq u(q_t^k) + \beta U_{aut} \tag{1.8}$$

holds in every period $t = 1, ...\infty$ for $k = 1, 2$.

The disutility of effort $g(a_t^k)$ cancels out from both sides of the inequality as the effort has already been exerted in period t, and thus it is the same in both the optimal contract (the left-hand side) and the autarky (the right-hand side) that starts in the current period.

The difference between the ex-ante and the ex-post limited commitment lies in the definition of the lower bound. Firstly, in the ex-ante commitment model the lower bound U_{aut} is the same in all states and all periods, while in the ex-post limited commitment model the lower bound fluctuates with output realizations. Secondly, the ex-post constraint (1.8) may be binding while the ex-ante constraint (1.7) may be slack for the same income realizations. Thus, in that sense, the ex-post limited commitment environment is more restrictive.

Let $U_k(\pi^{\infty,w_0})$ and $U_k(\pi^{\infty,w_0 \prime})$ be the expected lifetime utility that agent k obtains from the allocation assigned by π^{∞,w_0} and $\pi^{\infty,w_0 \prime}$, respectively. The following definition describes the standard notion of optimality of the contract that we use in this investigation.

Definition 1.3. An ex-ante (or ex-post) limited commitment contract π^{∞,w_0} is Pareto optimal (constrained-efficient) if π^{∞,w_0} is feasible, satisfies ex-ante limited commitment constraint (1.7) (or ex-post limited commitment constraint (1.8)), and there does not exist any other optimal ex-ante (or ex-post) limited commitment contract $\pi^{\infty,w_0\prime}$ such that $U_k(\pi^{\infty,w_0\prime}) \geq U_k(\pi^{\infty,w_0})$ with strict inequality for some $k = 1, 2$.

In Section 1.5 we provide a recursive formulation of limited commitment models, and in Section 1.7 we compare the ex-ante and ex-post environments after solving the models numerically.

1.4 The Private Information Economy

In this research we are also interested in the role of private information. When the individual effort levels are not publicly observable, the actions specified by some contracts are no longer enforceable. The agents can claim that they exerted the required effort even if they did not. There is a class of contracts that ensures that the agents take recommended actions. These contracts are called incentive compatible and they utilize the available information about output realizations. In the presence of private information, optimal consumption depends on output realizations because output is a noisy signal of the exerted effort. In general, the higher the output the more likely that the agent exerted higher effort.

The incentive constraints that the optimal contract has to satisfy are such that the agents willingly take the recommended action. That is, the optimal contract has to specify the consumption stream that rewards the agent when she exerts the optimal effort. In our definition of the incentive constraints we follow Sleet and Yeltekin (2001). Let $\delta = \{\delta^t\}_{t=0}^{\infty}$ and $\delta^t : \Omega^{t-1} \times A \to A$ be a deviation from the recommended action, and let π_δ^{∞,w_0} denote a probability measure that incorporates the deviation. Then define

$$\pi_\delta^{\infty,w_0}(\omega^t) \equiv \prod_{i=1}^{t} \frac{P(q_i \mid \delta_i(\omega^{i-1}, a_i))}{P(q_i \mid a_i)} \pi^{\infty,w_0}(\omega^t),$$

where the ratio of probabilities indicates how likely it is to get the output q_i with this deviating action relative to the recommended action a_i. Then the lifetime utility that the agent can get from deviating is given by:

$$U_\delta^k(\pi_\delta^{\infty,w_0}) = E_{\pi_\delta^{\infty,w_0}} \sum_{t=0}^{\infty} \beta^t \left[u(c_t^k) - g(\delta_t^k) \right].$$

Definition 1.4. The contract π^{∞,w_0} is incentive compatible if

$$U^k(\pi^{\infty,w_0}) \geq \sup_\delta U_\delta^k(\pi_\delta^{\infty,w_0}) \tag{1.9}$$

holds for $k = 1, 2$.

If the constraint (1.9) holds, then taking the recommended actions is in the agents' best interests. That is, the agents do not have any incentive to deviate from the prescribed action level. The contract that satisfies this constraint induces the recommended actions even though the actions are not publicly observable. In general, the levels of recommended actions will differ in the models with and without private information. The provision of incentives is costly as embodied by this constraint, and as current utility promises increase for agent 1, it becomes more difficult to motivate this agent to exert high effort. The opposite is true for agent 2, as his lifetime utility decreases in current utility promises.

At any date t, the consumption allocation depends only on the variables that are jointly observable at date t. It does not depend on individual effort levels, since they only are observable to an individual agent. Thus, consumptions of both agents at time t depend only on the history of income realizations. They do not depend on the history of past consumptions because we can solve back recursively and the consumption at time 1 depends only on incomes realized at time 1. The effort levels are chosen before the current period incomes are realized, and we can write them as $a_t^k(\omega^{t-1})$, $k = 1, 2$. The optimal effort levels do not depend on the history of consumption levels because we can solve recursively to show that time t effort will only depend on the history of incomes up to time t, ω^{t-1}. In addition, due to the utility being time separable, the optimal effort levels will not depend on the history of past chosen efforts.

In Section 1.5 we show how to transform the incentive constraints (1.9) into the recursive incentive constraints. Later in Section 1.8 we discuss the role of private information in limited commitment environments and how it changes the optimal allocations.

1.5 Recursive Contracts

In order to facilitate the analysis of dynamic contracts described in Sections 1.3 and 1.4, we transform the models into a recursive form. Here we concentrate on renegotiation-proof contracts, and thus all continuation contracts are also optimal. As in Spear and Srivastava (1987), we use the lifetime utility promise for agent 1 as a state variable and rewrite the problem recursively. The lifetime utility promise of agent 1 summarizes the history of output realizations in one variable, and thus it decreases the dimensionality of the maximization problems.

First we describe the timing of the model within the period. The agents enter the period with lifetime utility promise w and the value of providing this utility promise $U(w)$. Then the agents individually randomize over the action levels and receive their individual output realizations according to the stochastic production technology P. Then the contract prescribes the randomization over consumption c and future utility promises, w'. The agents consume their consumption shares and enter the next period with the future utility promise as a state variable.

Given the description above, the lottery contract is a probability distribution over recommended actions, $\pi(a)$, and a probability distribution over consumption and future utility promises conditional on output realizations, the recommended actions and the current utility promises, $\pi(c \mid a, q, w)$, $\pi(w' \mid a, q, w)$, where all the variables are two-dimensional vectors.

Assume that per-period utility is CRRA, i.e., $u(c) = c^{1-\gamma}/(1-\gamma)$, and the disutility function is $g(a) = \alpha a^2$. The output can take either high or low values: q^L

and q^H, and so does the effort: a^H and a^L. Let $\beta < 1$. The discretization of the space of consumption and utility promises implies that $W = \{w_1, ..., w_{nw}\} \in [U_{aut}, U_{\max}]$, $Q = \{q_i\}_{i=1}^{nq} = \{q^L, q^H\}$, $C = \{c_1, ..., c_{nc}\} \in [\varepsilon, 2q^H]$, and $A = \{a_i\}_{i=1}^{na} = \{a^L, a^H\}$. Here nw, nc, nq, and na denote the number of elements in the grid sets of utility promises, consumptions, outputs, and efforts, respectively. Then the lottery contract π is an object that has dimensions $na^2 \cdot nq^2 \cdot nc \cdot nw \times nw$. That is, each column of the lottery contract represents a probability distribution over available actions, outputs, consumption, and future utility promises for a given current utility promise w_i. Since the choice of optimal lottery contract for a given utility promise w does not alter the choice of optimal lottery contract for another utility promise, we can separate the overall maximization problem into smaller maximization problems associated with particular utility promises. Then the current utility promise w defines the current state (and fixes the column in π). Then $\pi(a^1, a^2, q^1, q^2, c, w') = \pi(a_i^1, a_i^2, q_i^1, q_i^2, c_i, w_i')$, where i denotes a particular row in a column associated with current state w, and gives the probability that the combination $(a_i^1, a_i^2, q_i^1, q_i^2, c_i, w_i')$ is optimal.

The contract in the ex-ante limited commitment model is given by π_{EA} such that π_{EA} satisfies the participation constraint that requires it to deliver agent 1 at least his current utility promise w, is consistent with the exogenous production technology, and satisfies the ex-ante limited commitment constraint. Similarly, the ex-post limited commitment contract is given by π_{EP}, and delivers agent 1 at least his current utility promise w, is consistent with the exogenous production technology P, and satisfies the ex-post limited commitment constraint. Finally, the limited commitment models with private information about efforts have to respect all the constraints mentioned above and additional incentive constraints. Now we will describe the recursive formulation of all these models.

The functional equation defines the objective function of the constrained optimization problem. Here $U(w)$ is the lifetime utility value of agent 2 given that the contract must guarantee at least w to agent 2. It is a recursive version of the equation (1.1):

$$U(w) = \max_{\pi} \sum_{A^2 \times Q^2 \times C \times W} \left\{ u(q^1 + q^2 - c) + \beta U(w') - g(a^2) \right\} \pi \left(a^1, a^2, q^1, q^2, c, w' \right). \tag{1.10}$$

The promise-keeping constraint (1.2) that requires that the contract delivers at least w has the following recursive representation. For all $w \in W$:

$$\sum_{A^2 \times Q^2 \times C \times W} \left\{ u(c) + \beta w' - g(a^1) \right\} \pi \left(a^1, a^2, q^1, q^2, c, w' \right) \geq w. \tag{1.11}$$

The constraint (1.3) that requires that the chosen probability distribution must be consistent with the exogenous technology for output, $p(y \mid a)$ is modified accordingly. For all $(\bar{a}^1, \bar{a}^2, \bar{q}^1, \bar{q}^2) \in A^2 \times Q^2$:

$$\sum_{C \times W} \pi \left(\bar{a}^1, \bar{a}^2, \bar{q}^1, \bar{q}^2, c, w' \right) = p(\bar{q}^1 \mid \bar{a}^1) p(\bar{q}^2 \mid \bar{a}^2) \sum_{Q^2 \times C \times W} \pi \left(\bar{a}^1, \bar{a}^2, q^1, q^2, c, w' \right). \tag{1.12}$$

In addition, each π must be a valid probability measure (the constraints (1.4) and

(1.5)):

$$\sum_{A^2 \times Q^2 \times C \times W} \pi\left(a^1, a^2, q^1, q^2, c, w'\right) = 1, \tag{1.13}$$

and for all $(a^1, a^2, q^1, q^2, c, w') \in A^2 \times Q^2 \times C \times W$:

$$\pi\left(a^1, a^2, q^1, q^2, c, w'\right) \geq 0. \tag{1.14}$$

Also we need to ensure that the agents' consumption is positive in the optimal contract:

$$c > 0, \tag{1.15}$$

$$y^1 + y^2 - c > 0. \tag{1.16}$$

In the models with limited commitment, the ex-ante limited commitment constraint (1.7) becomes

$$w' \geq U_{aut} \qquad w' \in W, \tag{1.17}$$

$$U(w') \geq U_{aut} \qquad U(w') \in W,$$

and the ex-post limited commitment constraint (1.8) becomes for all $(q^1, q^2) \in Q \times Q$

$$u(c) + \beta w' \geq u(q^1) + \beta U_{aut} \qquad w' \in W, \tag{1.18}$$

$$u(y^1 + y^2 - c) + \beta U(w') \geq u(y^2) + \beta U_{aut} \qquad U^2(w') \in W.$$

Due to the timing of the models, the action choice is the same on both sides of the constraint (1.18), and thus it cancels out. The constraints (1.15)-(1.18) do not involve the probability measure π directly. To ensure that this constraint is respected in optimal contract, we restrict those elements of π, for which consumption, utility promises outputs, and actions are such that the constraints are not satisfied, to be zeros. That is, the combination of $\{a^1, a^2, q^1, q^2, c, w'\} \in \Omega$ that does not satisfy the above constraints is assigned zero mass in optimal contract π.

In the models with private information, the incentive constraints (1.9) require that the lifetime utility from taking the recommended action is greater than from any other deviation. In our environment, there are only two actions available to each agent. Therefore, there are only four such incentive constraints. They are transformed in the following way. For all $(a^1, \tilde{a}^1) \in A$

$$\sum_{A\times Q^2\times C\times W} \left\{u(c) + \beta w' - g(a^1)\right\} \pi\left(a^1, a^2, q^1, q^2, c, w'\right) \tag{1.19}$$
$$\geq \sum_{A\times Q^2\times C\times W} \left\{u(c) + \beta w' - g(\tilde{a}^1)\right\} \frac{p(q^1 \mid \tilde{a}^1)}{p(q^1 \mid a^1)} \pi\left(a^1, a^2, q^1, q^2, c, w'\right),$$

and for all $(a^2, \tilde{a}^2) \in A$

$$\sum_{A\times Q^2\times C\times W} \left\{u(q^1 + q^2 - c) + \beta w' - g(a^2)\right\} \pi\left(a^1, a^2, q^1, q^2, c, w'\right) \tag{1.20}$$
$$\geq \sum_{A\times Q^2\times C\times W} \left\{u(q^1 + q^2 - c) + \beta w' - g(\tilde{a}^2)\right\} \frac{p(q^2 \mid \tilde{a}^2)}{p(q^2 \mid a^2)} \pi\left(a^1, a^2, q^1, q^2, c, w'\right).$$

1.5.1 Concavity of the Value Function

The introduction of lotteries convexifies the optimization problem. Here linear combinations (with weights that sum up to one) of π probabilities also satisfy the constraints above. But limited commitment constraints require special attention as they do not involve π directly. However, the contract π restrains the probability of the consumption-action combinations that are not feasible to be zero. This type of constraint is also linear and any linear combinations of π will satisfy such constraints.

That is, the linear combinations of choice variables are also feasible and belong to the constraint set. The objective function is weakly concave (linear) in the probabilities. Therefore, we can apply Theorems 4.6-4.9 in Stokey, Lucas, and Prescott (1989) to show that the value function is concave.

1.6 Parameterization

Given w, an optimal limited commitment contract is a probability distribution $\pi\left(a^1, a^2, q^1, q^2, c, w'\right)$ that maximizes the objective function (1.10) subject to constraints (1.11)-(1.16) along with the constraint (1.17) in the ex-ante commitment model and the constraint (1.18) in the ex-post commitment model. In the models with private information, the optimal contract also has to respect the incentive constraints (1.19) and (1.20).

Given the optimal probability distribution, we can use conditional and unconditional distributions $\pi(c|q^1, q^2)$, $\pi(w'|q^1, q^2)$, and $\pi(a^1, a^2)$ to derive policy functions for consumption, utility promises, and effort.

Table 1.1 summarizes the values of the parameters that are used in numerical computations.

It is straightforward to compute the value of autarky. In autarky, each period from time t looks the same as period t before the output realization. This is essentially a static problem. Since there are only two levels of effort available, we have to compare the lifetime utility from always exerting high effort and the lifetime utility from always exerting low effort, then choose the highest of the two numbers. In

Table 1.1: Parameterization

Parameters	Value	Name
β	0.98	discount factor
γ	1.5	risk aversion parameter
$p(q^H \mid a^H)$	0.72	$\Pr[q^H \mid a^H]$
$p(q^L \mid a^H)$	0.28	$\Pr[q^L \mid a^H]$
$p(q^H \mid a^L)$	0.28	$\Pr[q^H \mid a^L]$
$p(q^L \mid a^L)$	0.72	$\Pr[q^L \mid a^L]$
α	2.5	disutility parameter
q^H	3	high output
q^L	0.5	low output
a^H	0.6	high effort
a^L	0.2	low effort
nc	various	grid, consumption
nw	various	grid, utility promises

our parameterization, the agent always exerts high effort and the value of autarky is equal to -63.08. This is the lower bound on utility promises in the ex-ante limited commitment model. In the ex-post limited commitment model, the lower bound on the sum of the current utility plus discounted future utility promise fluctuates between -63.39 and -61.72 depending on the output realization.

1.7 Results: Ex-Ante vs. Ex-Post Commitment

This section compares the optimal contracts in ex-ante and ex-post limited commitment models. Section 1.8 studies how the optimal contract changes when the actions are no longer publicly observed. Figures 1.1 through 1.5 show the solutions to both ex-ante and ex-post limited commitment models.

We find that the two models are very similar in terms of their predictions.

The difference between them is in the optimal behavior near the bounds. The ex-ante limited commitment constraints are not as restrictive as ex-post limited commitment constraints. In our parameterization, the autarky level is -63.08, while the ex-post commitment bounds are -63.39 and -61.72 depending on the output realization. This implies that there are more states of the world in the ex-post commitment model that are binding. Qualitatively, the predictions of both models are the same.

A version of the ex-post commitment model has been studied in Kocherlakota (1996). There is no output production, and thus no action choice in Kocherlakota's model. Our results are consistent with Kocherlakota (1996) even in the presence of production. We find that unless one of the agents is constrained, the first best solution (in our models the output is shared equally) is obtained. However, when one of the agents is close to his upper bound (and the other agent is close to his lower bound), his high current utility promise can be fulfilled only by increasing his current consumption. This implies that the agent on the lower bound has to share his output. Since this agent's current utility promise is so low, he is compensated with future utility promise that is high enough to keep him in the contract.

In the long-run, the distribution of utility promises becomes degenerate, with all the mass concentrated on some value within the limited commitment bounds. We do not observe one agent being driven to his lower bound as in the "immiserization" steady state. Also, only one of the agents exerts higher effort in the steady state. These predictions differ in the environments with private information. Section 1.8 discusses the differences in greater detail.

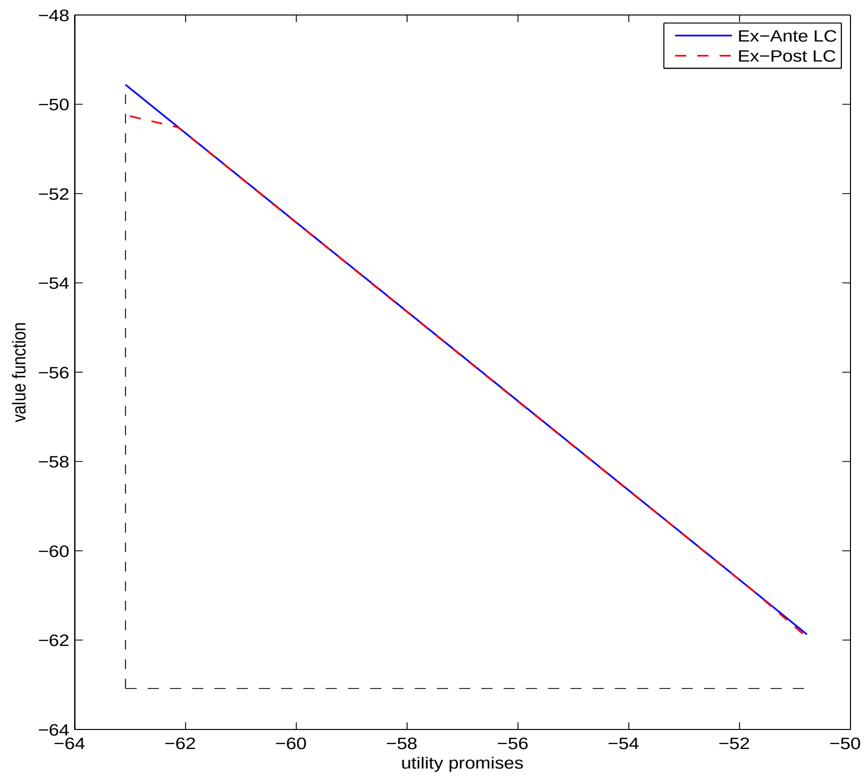
1.7.1 Value Functions

In Figure 1.1 we compare the value functions $U(w)$ for both ex-ante and ex-post limited commitment models. The x-axis is utility promises to agent 1 at the beginning of the current period. The vertical (horizontal) dashed black lines shows the autarky value U_{aut} for agent 1 (agent 2). As we speculated in Section 1.3.3, in the ex-post limited commitment environment the agents are more constrained because the ex-post limited commitment value function lies uniformly below the ex-ante limited commitment value function. In terms of risk-sharing, this means that the ex-post commitment model exhibits less risk-sharing than the ex-ante commitment model. This is due to the bounds on utility promises being tighter in the former. Since this is a production economy, the optimal contract would use the spread in utility promises to induce the required action. But near the bounds, there is a limit to such spread.

1.7.2 Consumption

Figure 1.2 displays the consumption policy functions computed as conditional expectations, $E(c \mid q^1, q^2)$. The upper panel shows the optimal consumption in the ex-ante limited commitment model, while the lower panel shows the ex-post commitment model. When both agents realize the same output and neither of the agents is near the bounds, then they each consume their own outputs. The risk-sharing comes into play when the agents' output realizations differ in the current period. There are such values of state variable w, that both agents just split the aggregate consumption in half. This is not surprising because the agents are identical. In the ex-post commitment model,

Figure 1.1: Value Functions in Ex-Ante and Ex-Post Limited Commitment Models. The vertical (horizontal) dashed black line shows the autarky value U_{aut} for agent 1 (agent 2)



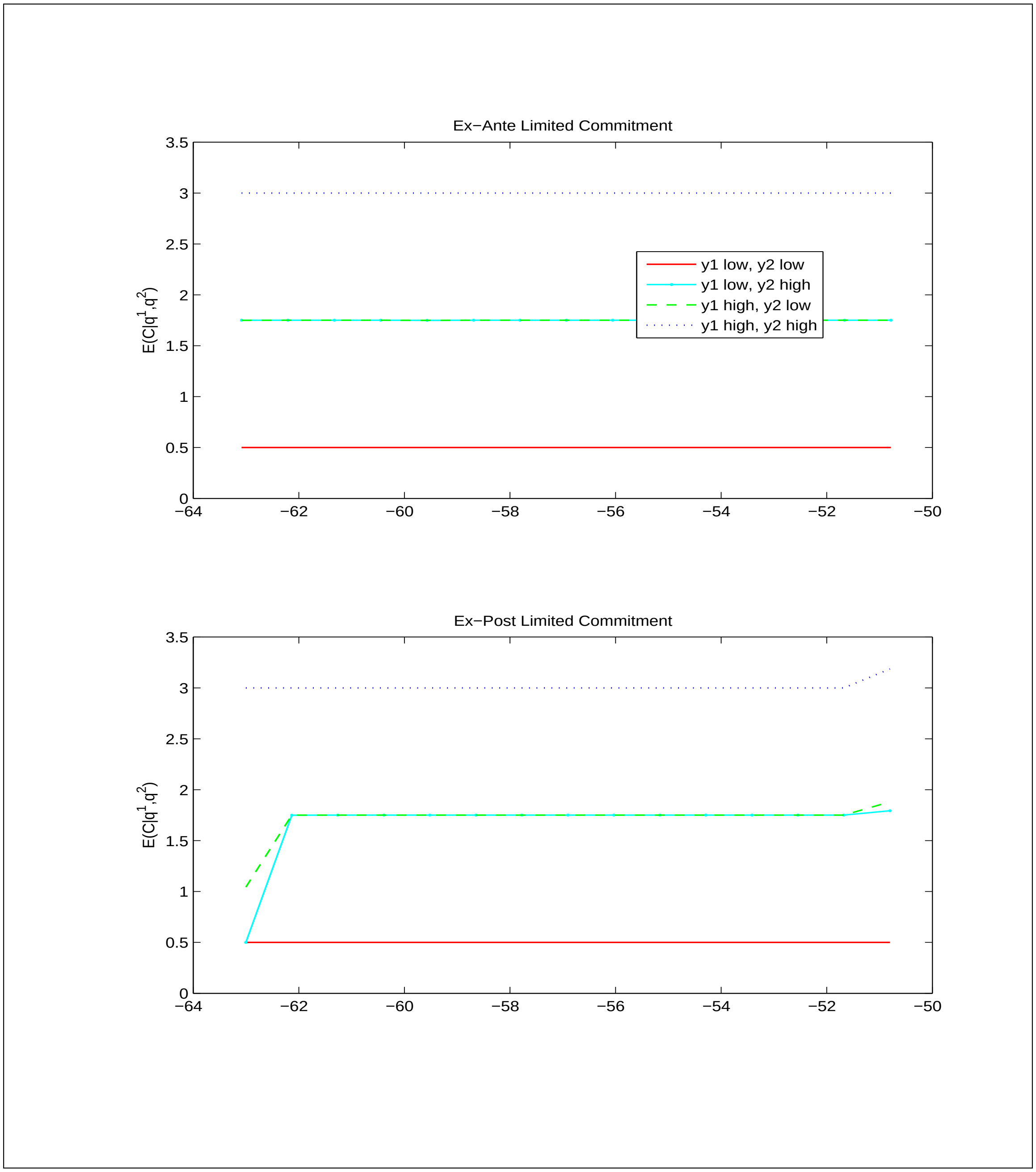
if agent 1 realized low output while agent 2 realized high output, then the optimal contract prescribes a decrease in agent 1's consumption. This is because agent 2 came into the period with very high utility promise close to $U(U_{aut})$, and the only way to fulfill that promise is to decrease agent 1's consumption and increase his utility promise. Since agent 1 realized low output, he is indifferent between autarky and the contract. The contract rewards him with higher future utility promise. This decrease in consumption is not present in the ex-ante limited commitment model.

1.7.3 Utility Promises and Efforts

Figure 1.3 displays the utility promises computed as conditional expectations, $E(w' \mid q^1, q^2)$ and recommended actions, computed as unconditional expectations $E(a)$. The left panel shows the optimal utility promises in the ex-ante limited commitment model, while the right panel shows the one in the ex-post commitment problem. Apart from the variability in policy functions that comes from coarseness of the grid, an interesting observation emerges.[2] There is such a level of utility promises w^* that if agent 1's current utility promise is below w^*, then he is assigned higher action. Otherwise, agent 2 has to take higher action. This observation is consistent with leisure being a normal good. As the current utility promises of the agent increase, he becomes "richer" in lifetime utility sense, and it becomes very costly to keep him working. This explanation is supported in the lower panel of Figure 1.3,

[2] Grid lotteries are lotteries over adjacent grid points. Prescott (1999) points out that they often appear in such computations. These variations have no economic meaning and are present due to finiteness of the grids.

Figure 1.2: Consumption in Ex-Ante and Ex-Post Limited Commitment Models



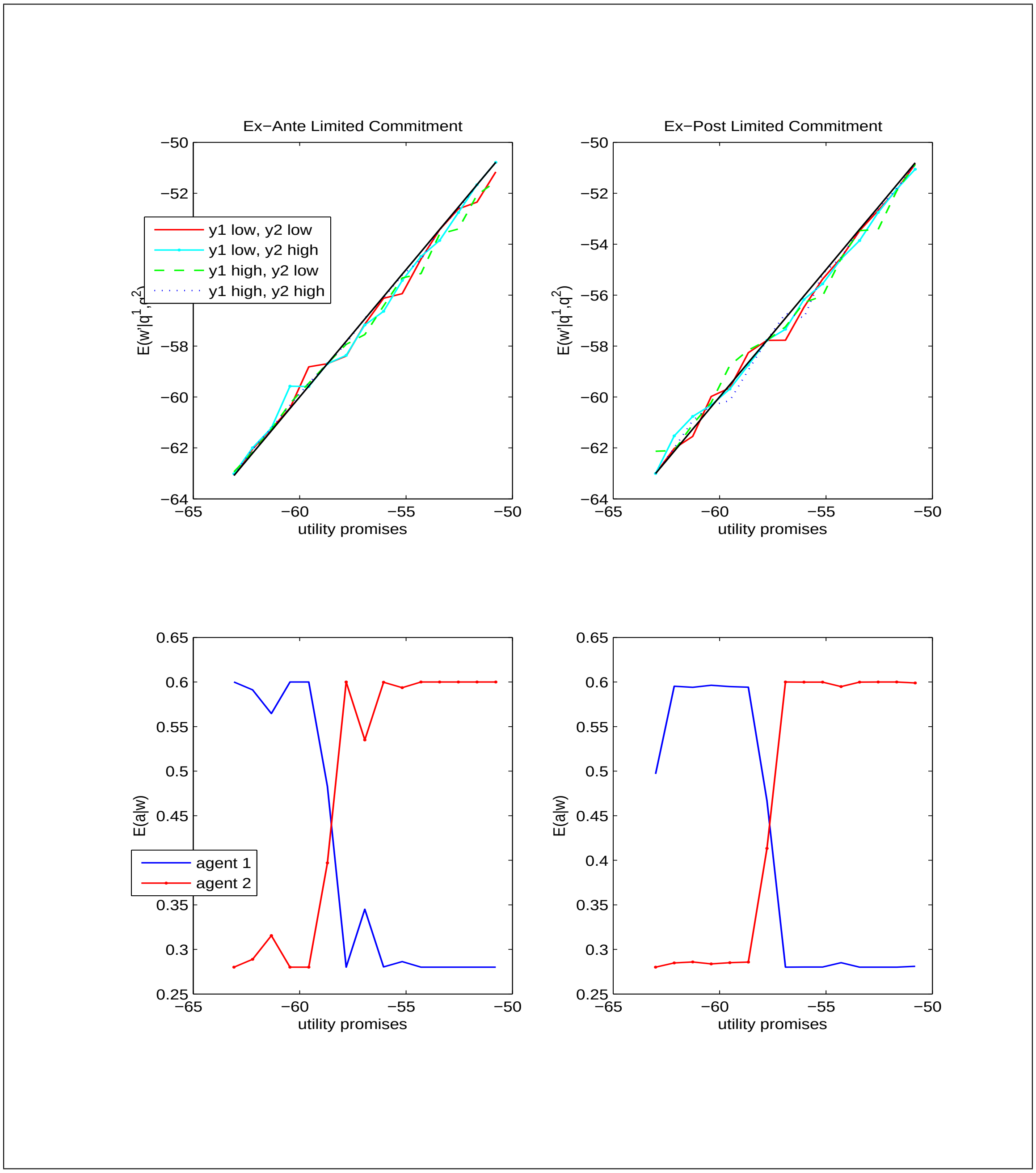
where the recommended actions are shown. Around w^*, there is a switch in the roles of the agents: One of the agents starts exerting higher effort, and the other one lower effort.

Interestingly, although the actions are publicly observable, and any recommended action can be enforced, the utility promises still show the variation. This feature is particular to this model. The two agents are identical and risk-averse, and the optimal contract has to respect this. There is also production that requires effort. In a model with endowment shocks (like Kocherlakota (1996)), there is no effort and as a result, there is no need in the variation of utility promises for some income realizations. In fact, in an endowment economy, there is a range of income realizations for each current utility promise that perfect risk-sharing is achieved on that interval. We do not observe this here.

1.7.4 Invariant Distributions and Effort Transitions

Figure 1.4 displays the invariant distributions of utility promises and efforts, while Figure 1.5 shows the invariant distributions of consumption and aggregate output. One of the discussions in the literature on contracts with limited commitment and/or private information is that without lower bounds, the steady-state utility promise and consumption distributions become degenerate, and one agent consuming everything and the other agent nothing. The limited commitment environment does not produce such an "immiserization" result. The invariant distributions here converge to absorbing states, that are not near the boundaries U_{aut} and $U(U_{aut})$, but

Figure 1.3: Utility Promises and Efforts in Ex-Ante and Ex-Post Limited Commitment Models



rather, are close to the middle of the interval. The optimal contract prescribes that only one agent works in the steady state. Since the efforts are observable, they can actually be implemented. When the efforts are not observable, both agents work in the steady-state.

In Figure 1.5 we show the steady-state distribution of consumption and aggregate output. The distribution is clustered around q^L, $0.5(q^H + q^L)$, and q^H. The expected aggregate output differs across these economies. For our parameterization, the expected aggregate output is 3.47 in the ex-ante limited commitment model, and 3.59 in the ex-post limited commitment model.

Table 1.2: Transition Probability Matrix: Effort Levels of Agent 1. Ex-Ante (upper panel) and Ex-Post (lower panel) Limited Commitment Models

Ex-Ante LC	$s_{t+1} = a^L$	$s_{t+1} = a^H$
$s_t = a^L$	0.95	0.05
$s_t = a^H$	0	1
	Steady- State Probability Matrix	
	$s_t = a^L$	$s_t = a^H$
	0	1
Ex-Post LC	$s_{t+1} = a^L$	$s_{t+1} = a^H$
$s_t = a^L$	0.91	0.09
$s_t = a^H$	0	1
	Steady- State Probability Matrix	
	0	1

To study the fluctuations in optimal efforts, it is useful to construct a transition matrix. In particular, for each model we simulate 500 life histories for 2,000 periods.

Figure 1.4: Invariant Distributions in Ex-Ante (left column) and Ex-Post (right column) Limited Commitment Models: Utility Promises (top two rows) and Effort (bottom two rows). The red line denotes the autarky

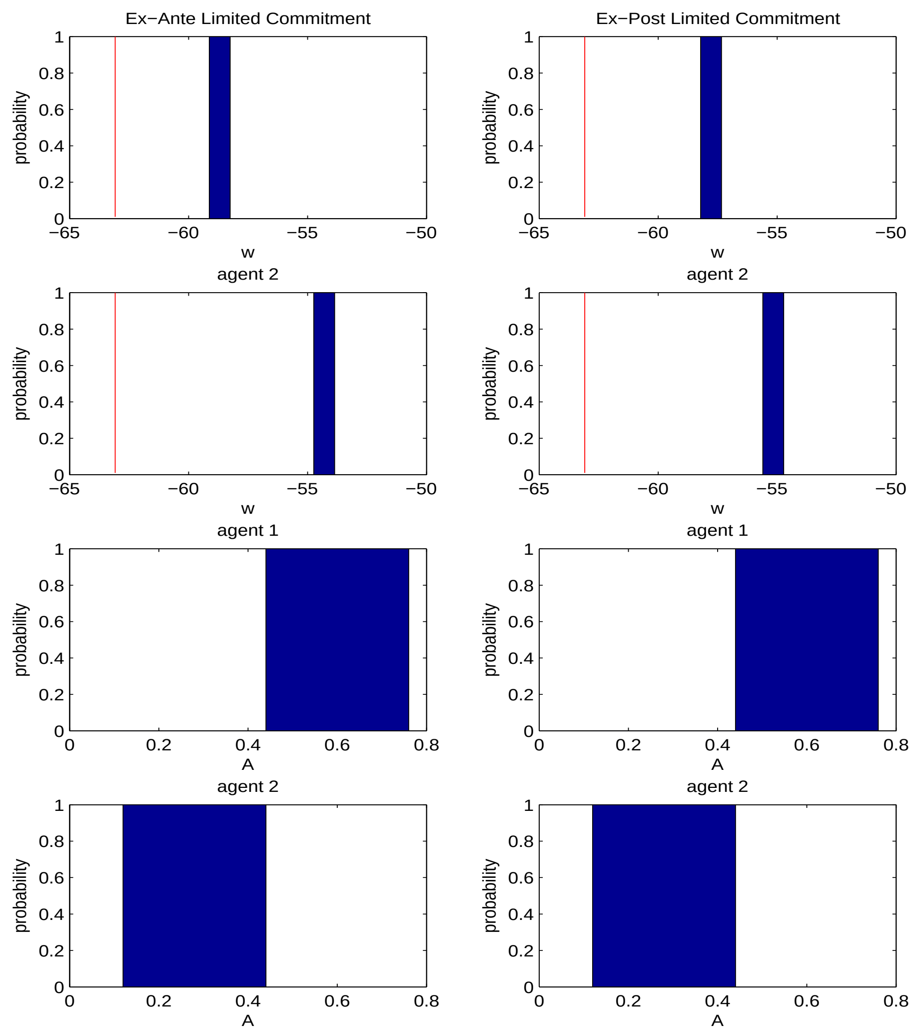
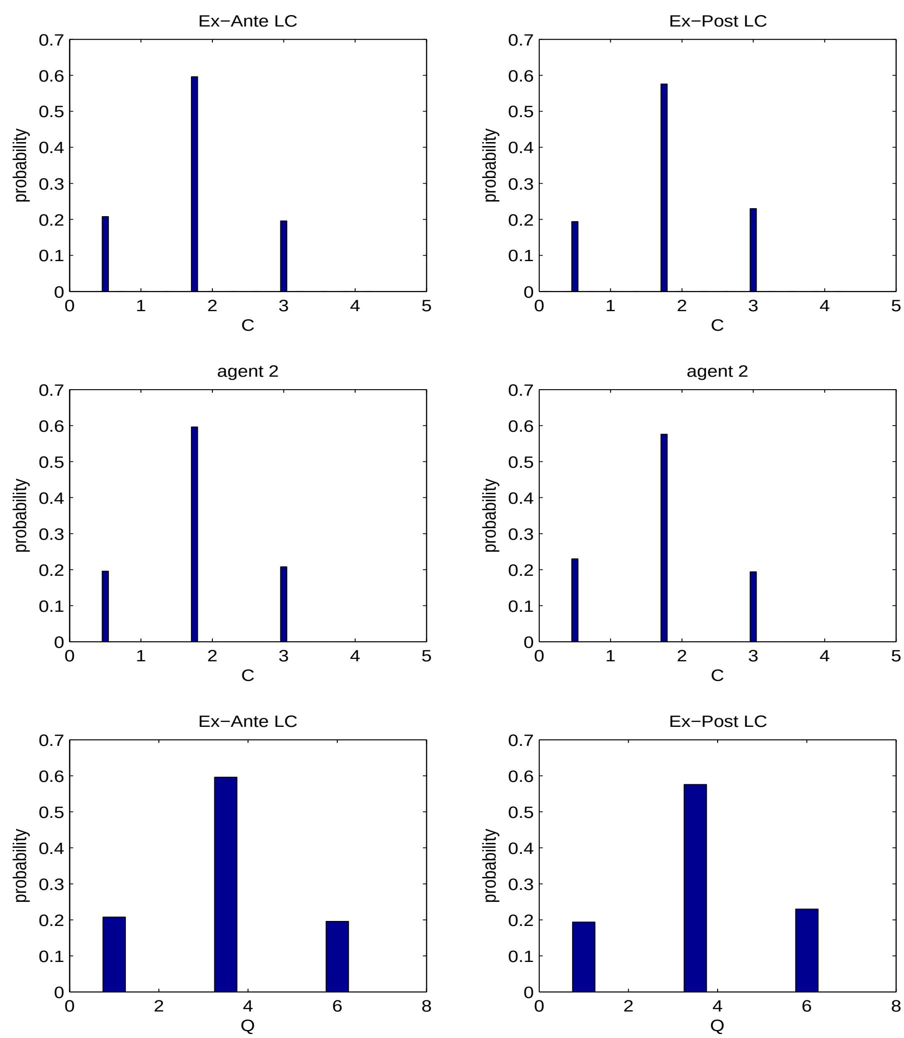


Figure 1.5: Invariant Distributions in Ex-Ante (left column) and Ex-Post (right column) Limited Commitment Models: Consumption (top two rows) and Aggregate Output (bottom row)



For each life-history, we count the transitions from a_L to a_H. Later, we take the mean of all 500 counts and divide by the sum of counts that describe the transitions from high to low, provided that effort a_L or a_H was recommended in the current period. Then Table 1.2 provides the transition matrices for the effort processes in both models. The steady-state distributions of the transition matrices are shown in the third row of Figure 1.4. The transition probability matrices confirm the degenerate steady-state distribution of optimal efforts.

1.8 Results: The Role of Private Information

The introduction of unobservability of actions adds additional constraints on the value function and it lowers the surplus available to the agents as the expected output goes down. It also leads to a greater variability in consumption and changes the long-run properties of the contract.

In general, both ex-ante and ex-post limited commitment models with private information produce very similar predictions about policy functions and steady-state distributions. A common result emerges: When the efforts are not observable, it is optimal to induce both agents to work in the steady-state. This is in contrast to the predictions of the limited commitment models with full information. In the latter environments, it is optimal to have only one agent working in the steady-state. Because now the contract has to punish the agent if his output realization is low, and reward him if it is high, there is a small variability in the steady-state utility promises. Even though the invariant distributions of utility promises are still degenerate (as in the full information models), there are now more states that are absorbing, and they are all concentrated toward the middle of the interval $[U_{aut}, U_{max}]$. The difference between the steady-state lifetime utilities of agent 1 and agent 2 also decreases, indicating that if each agent is valued equally in these models, then the steady-state distribution of life-time utilities becomes "fairer."

In addition, optimal consumption patterns also exhibit greater variability near the lower and upper bounds than in the models with only limited commitment. Not only individual consumption varies because of commitment constraints, now it also helps with incentives for work. For example, consider the case when agent 1 is near his lower bound on utility promises. In the models with only limited commitment, the agent receives higher utility promise in order to compensate for the decrease in his consumption (that goes as a transfer to agent 2 to keep him from breaking the contract). This is true even if his output realization is low. In the limited commitment models with private information, the agent has to be punished for the low output realization, and his utility promise has to decrease. But if he is near his lower bound, this puts a limit on how much his future utility promise can be decreased. In the extreme case of agent 1 being promised $w = U_{aut}$ in the current period, the future utility promise w' cannot go lower than what he is promised in the current period. Then agent 1's consumption has to decrease in order to create proper incentives for work.

In the long-run, both private information and full information limited commitment models predict similar steady-state distribution of consumption that has three absorbing states: q^L, $0.5(q^H+q^L)$, and q^H. This result is a stark contrast to the results in other models with private information (for example, Thomas and Worrall (1990)), where the steady- state consumption is concentrated on a lower bound. Since our steady-state distribution is similar in full information and private information models (the expected consumption is lower in private information models), we conclude that this is the result of our economy being closed and both agents being risk-averse.

Sections 1.8.1 through 1.8.3 discuss in more detail the predictions of the models with and without private information.

1.8.1 Moral Hazard in the Ex-Ante Commitment Model

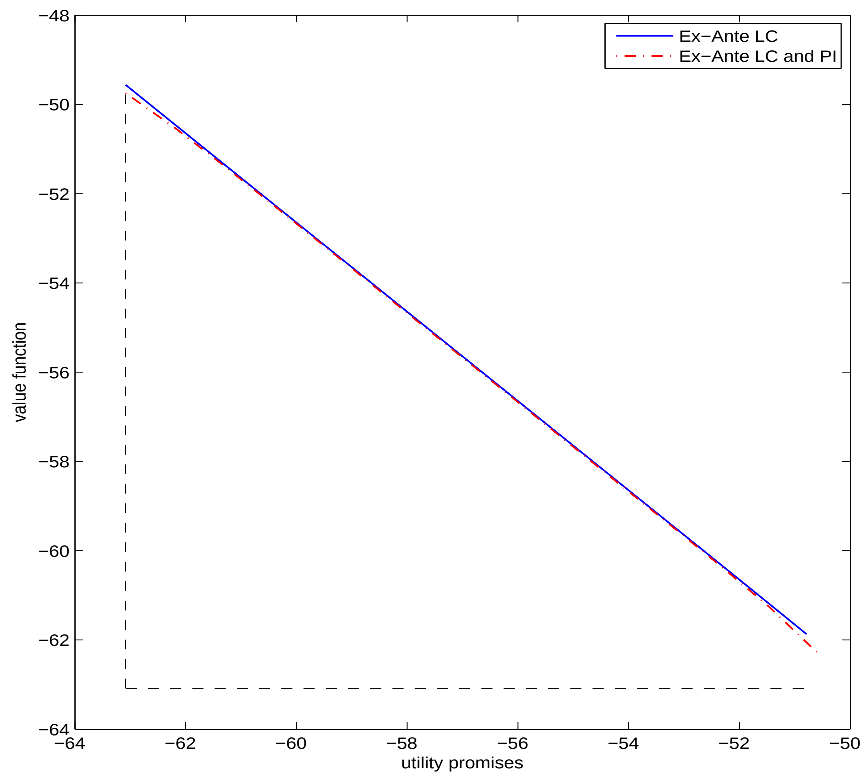
1.8.1.1 Value Functions

Figure 1.6 compares the value functions of the ex-ante limited commitment model with and without private information. The vertical (horizontal) dashed black lines shows the autarky value U_{aut} for agent 1 (agent 2). As expected, the incentive compatibility decreases the surplus and lowers the value function when the actions are not observable. Otherwise, the value functions are concave and decreasing, implying that the only way to give more future consumption to one of the agents is by decreasing future consumption of the other agent.

1.8.1.2 Consumption

Figure 1.7 displays the consumption policy functions computed as conditional expectations, $E(c \mid q^1, q^2)$. The upper panel shows the optimal consumption in the ex-ante limited commitment model, while the lower panel shows the ex-ante commitment

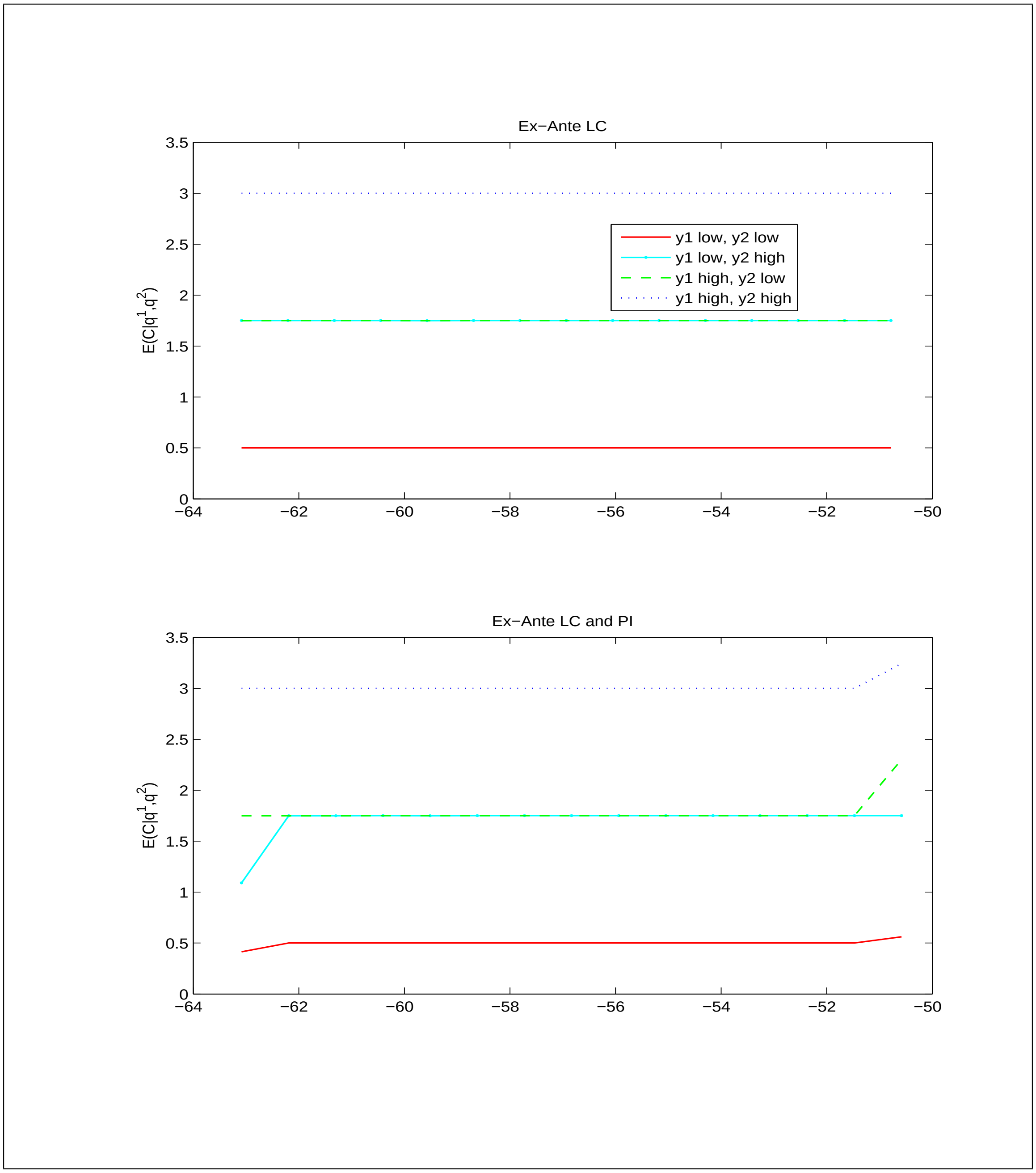
Figure 1.6: Value Functions in Ex-Ante Limited Commitment and Private Information Models. The vertical (horizontal) dashed black line shows the autarky value U_{aut} for agent 1 (agent 2)



problem with private information. In the presence of private information, we observe a strong resemblance to results of the standard principal-agent model: When agent 1 realizes low output and agent 2 realizes high output, agent 1 is punished by a decrease in his current consumption and agent 2 is rewarded with higher consumption. The utility promise of agent 2 does not increase because it is impossible to have a spread in future utilities for agent 2 near the higher bound of the utility promises. In a private information environment, the need for rewards and punishments near the bounds introduces variability in optimal consumption near the bounds.

When both agents are away from the lower and upper bounds of their utility promises, they split the aggregate output in half. Now, in the case when agent 1 is close to his upper bound for utility promises and he realizes higher output than agent 2, then agent 1 is given higher consumption (his future utility promise cannot go up by much because he is close to his upper bound). This is due to agent 1 having such a high current utility promise $w = U(U_{aut})$. The only way to fulfill this promise is to give him more consumption. This is the limited commitment part of the increase in agent 1's consumption. Since he also realized higher output than agent 2, he has to be rewarded with both higher consumption and higher utility promise w'. However, he is near the upper bound, so only his consumption can be increased. This leads to an even bigger increase in agent 1 consumption. That is why we observe more variability across states when both limited commitment and private information are present.

Figure 1.7: Consumption in Ex-Ante Limited Commitment and Private Information Models



1.8.1.3 Utility Promises and Efforts

The presence of private information creates a distinctive pattern in utility promises, as evident in Figure 1.8. The utility promises are computed as conditional expectations $E(w' \mid q^1, q^2)$, and recommended actions are computed as unconditional expectations $E(a)$. The left panel in Figure 1.8 shows the optimal future utility promises in the ex-ante limited commitment model without private information, while the right panel shows utilities for the ex-ante commitment problem with private information. The upper row shows the utility promises and the lower row shows optimal effort levels. In the model with private information, agent 1 cannot be punished below the autarky level when he realizes output that is lower than agent 2's (light blue line in the utility promise panel). Therefore, the contract varies his consumption.

The pattern of utility promises is similar to the standard principal agent model: Reward the agents when they have high output, and punish them when the outputs are low. As before, there is one distinctive feature: Utility promises go on or below the 45 degree line for some w^* (that is, below his current utility promise w). This implies that it is too costly to make agent 1 work when his utility promise is above w^*. In that region of utility promises, the effort of agent 1 switches to the lowest level possible, and agent 2 starts exerting higher effort. This is the result of our particular double-sided model. This corresponds to a more general result in principal-agent models: As the current utility promises increase, the "wealth" effect increases leisure (a normal good) and decreases effort. In other words, it is costlier to create a spread in utilities to motivate the agent when he is promised high life-time utility than when he is promised a low life-time utility. Zhao (2007) studies the model with ex-ante commitment and private information. Although he does not report the policy functions, his simulated life-time utility promises and efforts exhibit the same pattern: As utility promises increase, the recommended efforts decrease.

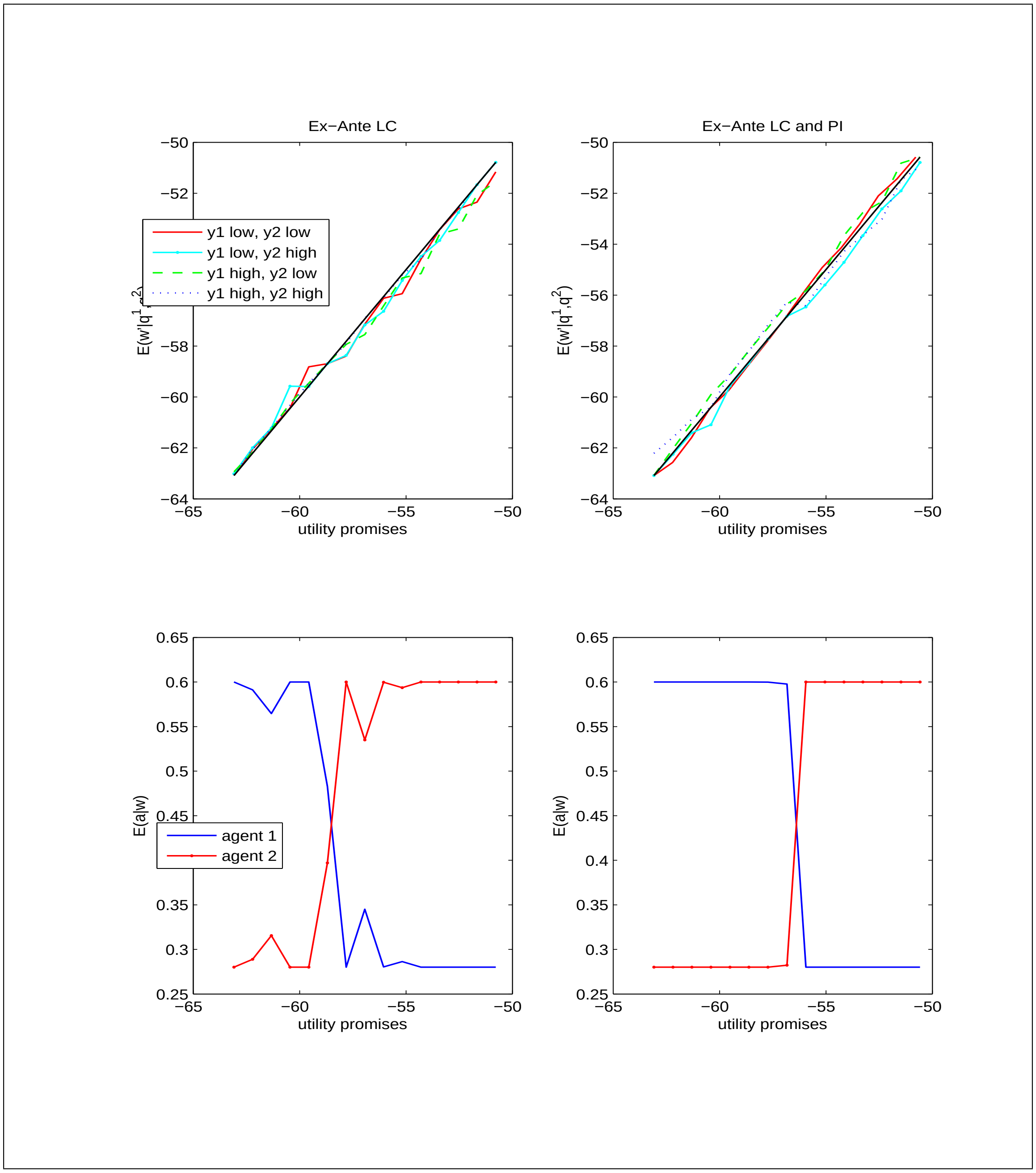
1.8.1.4 Invariant Distributions and Effort Transitions

Figure 1.9 displays the invariant distributions of utility promises and efforts, while Figure 1.10 shows the invariant distributions of consumption and aggregate output. The left panels in Figures 1.9 and 1.10 show the distributions in the ex-ante limited commitment model without private information, while the right panels show the distributions for the ex-ante commitment problem with private information. In Figure 1.9, the upper four panels show the steady-state distributions of utility promises of agent 1 (the first row) and agent 2 (the second row). The last two rows show the steady-state distributions of effort for agent 1 and agent 2.

While the invariant distribution of utility promises in the ex-ante commitment model converges to some absorbing state, the invariant distribution in a model with private information has more absorbing states. The mass is located closer to the middle of $[U_{aut}, U_{max}]$. This is similar to the findings of Zhao (2007), who finds that the utility limits act as reflecting barriers and the utility promises bounce back into the interior of the set after hitting the bounds. In the long-run the actual bounds between which the utility promises fluctuate are much higher than the autarky value.

The stark difference is in the optimal recommendations for efforts. In the full

Figure 1.8: Utility Promises and Efforts in Ex-Ante Limited Commitment and Private Information Models



information ex-ante limited commitment model, agent 1 always exerts higher effort and is poorer (his distribution is more to the left in top row) in terms of steady-state utility promise, while agent 2 is exerting lower effort and is richer in terms of life-time utility. That is, we observe "working poor" and rich agents. In contrast, in the model with private information, both agents are recommended to work, and the spread in the steady-state utility promises decreases (agent 1's distribution shifts to the right in top row). The model society with equal treatment of agents becomes "fairer."

The steady-state distributions of consumption and aggregate output are similar in both full information and private information environments. The difference lies in the expected steady-state consumption and output. In the model with ex-ante limited commitment and private information, the expected aggregate output is 3.41, which is lower than 3.47 in the full information version. As said before, some of the potential surplus is lost to provide proper incentives.

We also compare the transition probability matrices for effort processes for these models. They are given in Table 1.3. In the full information limited commitment model, agent 1 works most of the time, while in the model with private information, both agents work almost equally in a steady-state.

1.8.2 Moral Hazard in the Ex-Post Commitment Model

1.8.2.1 Value Functions

Figure 1.11 compares the value functions of the ex-post limited commitment model with and without private information. The vertical (horizontal) dashed black

Figure 1.9: Invariant Distributions in Ex-Ante (left column) and Ex-Ante with Private Information (right column) Limited Commitment Models: Utility Promises (top two rows) and Effort (bottom two rows). The red line denotes the autarky

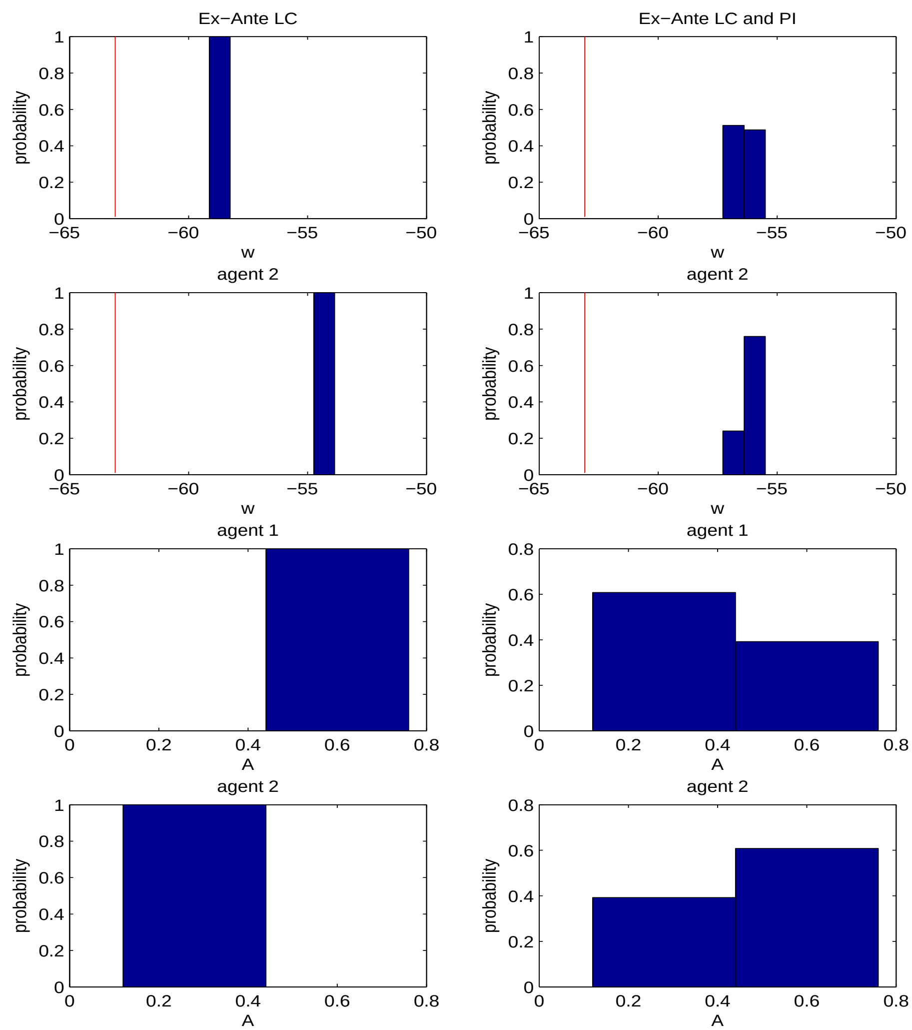


Figure 1.10: Invariant Distributions in Ex-Ante (left column) and Ex-Ante with Private Information (right column) Limited Commitment Models: Consumption (top two rows) and Aggregate Output (bottom row)

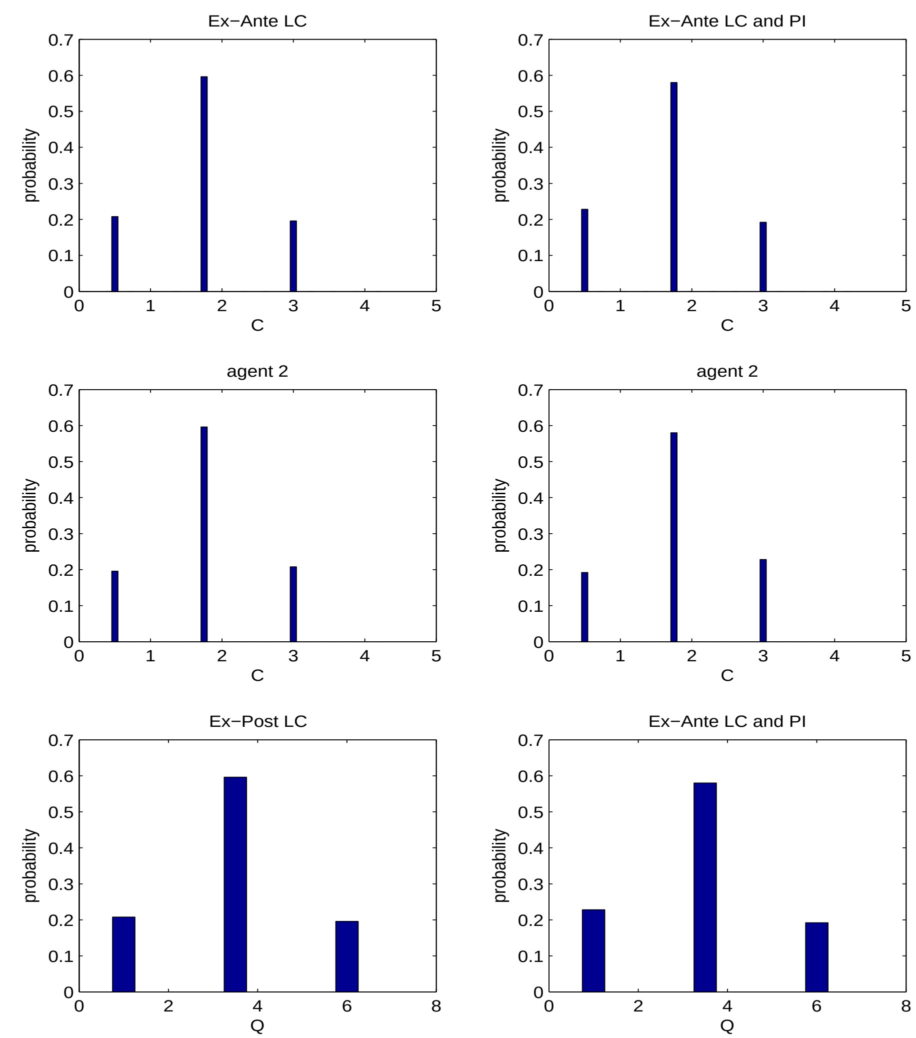


Table 1.3: Transition Probability Matrix: Effort Levels of Agent 1. Ex-Ante (upper panel) and Ex-Ante with Private Information (lower panel) Limited Commitment Models

Ex-Ante LC	$s_{t+1} = a^L$	$s_{t+1} = a^H$
$s_t = a^L$	0.95	0.05
$s_t = a^H$	0	1
	Steady-State Probability Matrix	
	0	1
Ex-Ante LC and PI	$s_{t+1} = a^L$	$s_{t+1} = a^H$
$s_t = a^L$	0.49	0.51
$s_t = a^H$	0.71	0.29
	Steady-State Probability Matrix	
	0.58	0.42

lines shows the autarky value U_{aut} for agent 1 (agent 2). As before, the incentive compatibility decreases the surplus and lowers the value function when the actions are not observable.

1.8.2.2 Consumption

Figure 1.12 displays the consumption policy functions computed as conditional expectations, $E(c \mid q^1, q^2)$. The upper panel shows the optimal consumption in the ex-post limited commitment model, while the lower panel shows the ex-post commitment problem with private information. Similar to Section 1.8.1, we find an increase in consumption variability across states near the bounds on utility promises. Near the upper bound of the utility promises, it is impossible to have a spread in future utilities, and as a result, the contract introduces variability in consumption. When agent 2 is close to his upper bound for utility promises, he is rewarded when he gets higher

Figure 1.11: Value Functions in Ex-Post Limited Commitment and Private Information Models. The vertical (horizontal) dashed black line shows the autarky value U_{aut} for agent 1 (agent 2)

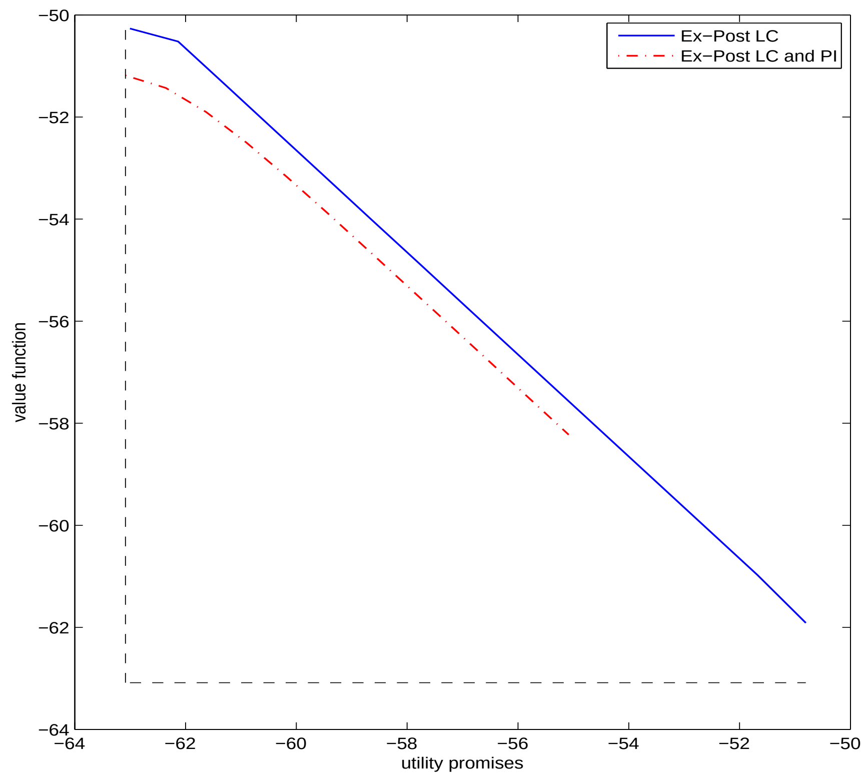
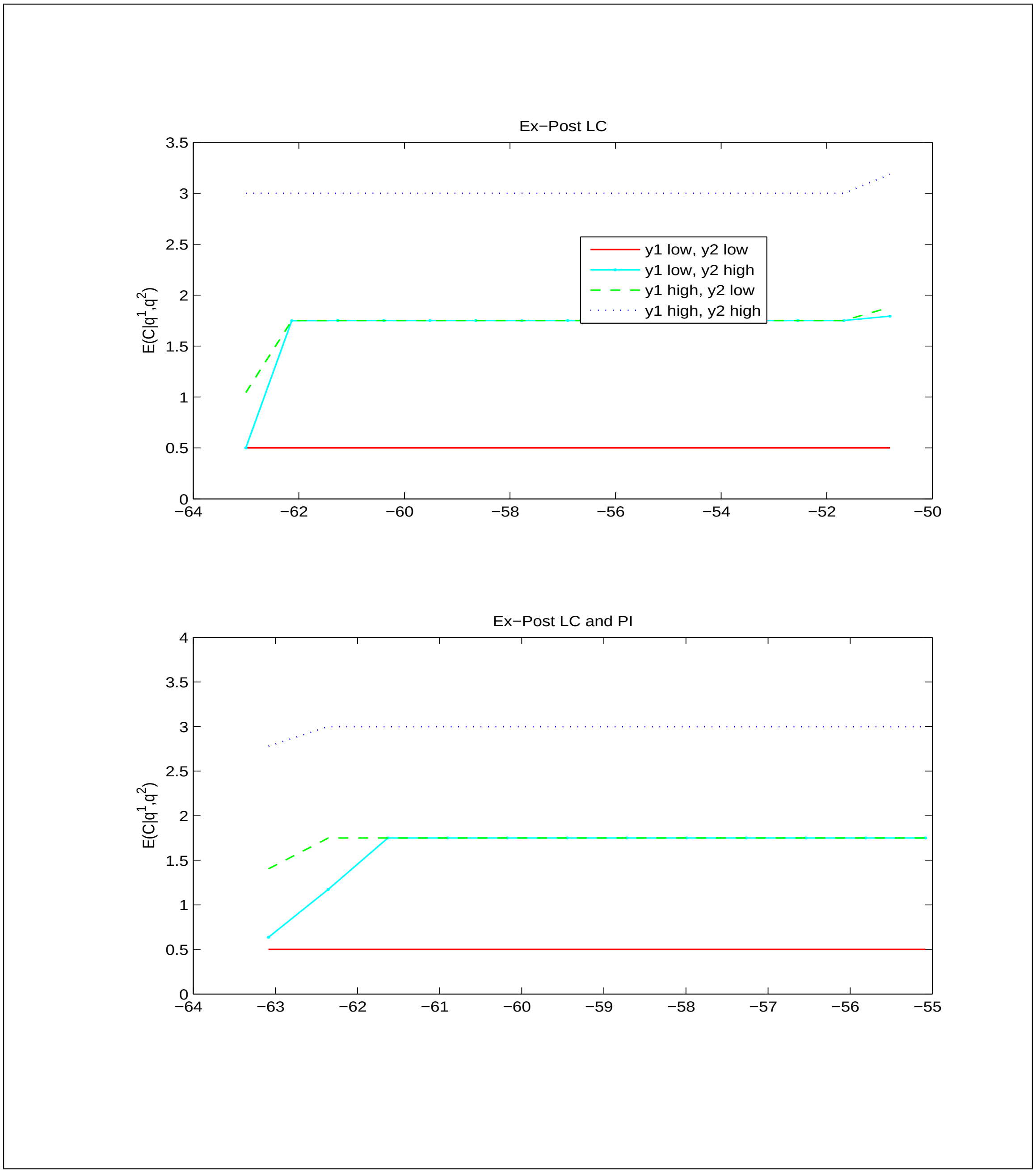


Figure 1.12: Consumption in Ex-Post Limited Commitment and Private Information Models



output than agent 1. Because agent 2 has such a high utility promise, the only way to fulfill this promise is to give him more consumption. The contract cannot also give him more of the future utility because agent 1 is at his lower bound, and his utility cannot be pushed down. Since the aggregate output is equal to aggregate consumption, the consumption of agent 2 goes up. When agent 1 is close to his lower bound, he is rewarded if he realizes high output (the green line is above the blue line), but because agent 2 has a high utility promise, the only way to keep that promise is by giving him more consumption. Therefore, even though agent 1 has a high output realization, he has to share it with agent 2. Optimal consumption in the full information ex-post limited commitment model does not exhibit such variations.

1.8.2.3 Utility Promises and Efforts

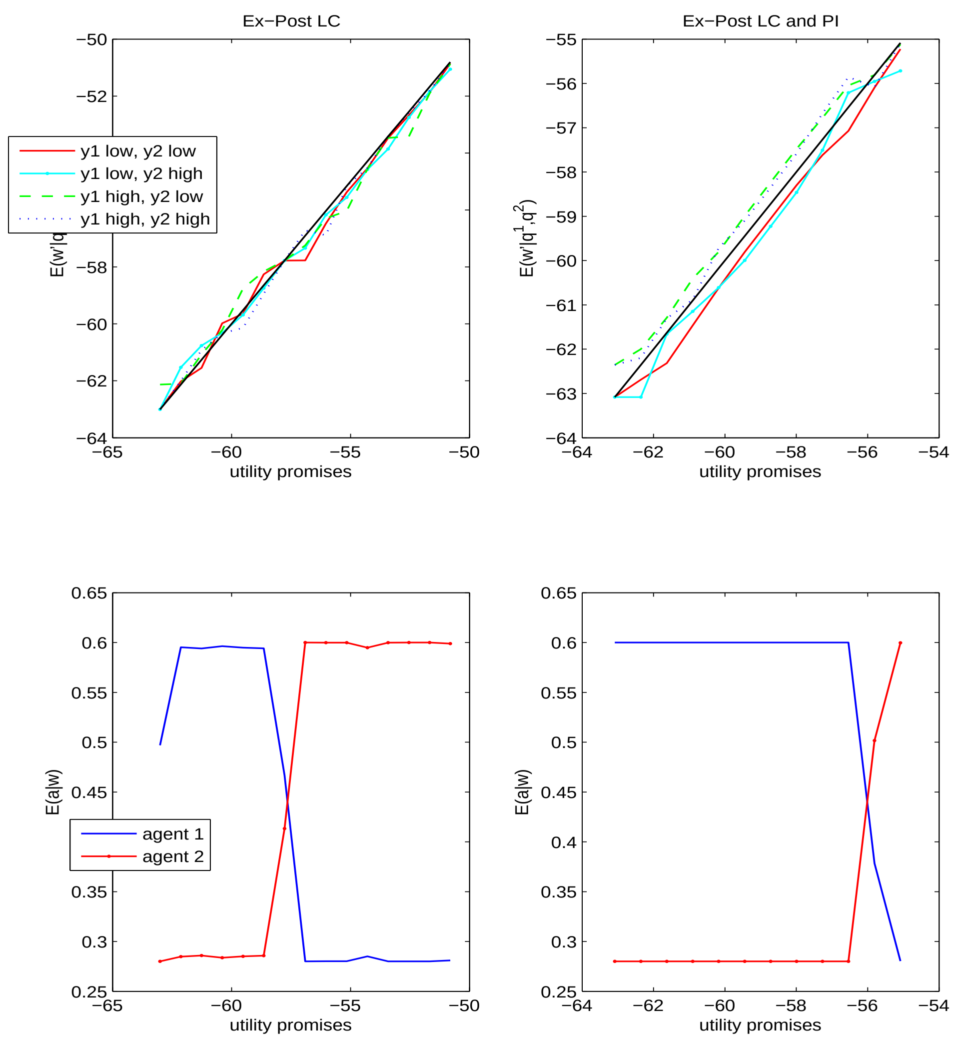
The presence of private information creates a distinctive pattern in utility promises, as shown in Figure 1.13. The utility promises are computed as conditional expectations, $E(w' \mid q^1, q^2)$ and recommended actions are computed as unconditional expectations $E(a)$. The left panel in Figure 1.8 shows the optimal future utility promises in the ex-post limited commitment model without private information, while the right panel shows utilities for the ex-post commitment problem with private information. The upper row shows the utility promises and the lower row shows optimal effort levels. The prediction of the model with ex-post limited commitment and private information are very similar to the predictions of the model with ex-ante limited commitment and private information. The variability of optimal consumption increases in the former, as the agents cannot be punished in more states (the lower bounds are now -63.39 and -61.72, compared to the value of autarky -63.08). But if the agent near autarky gets high output (even if the other agent gets higher output as well), he is immediately rewarded with higher future utility promise.

Again, in the model with private information, agent 1 cannot be punished below the autarky level when he realizes output that is lower than agent 2's (blue line in the utility promise panel). Therefore, the contract varies his consumption. The pattern of utility promises is similar to the standard principal agent model: Reward the agents when they have high output, and punish them when the outputs are low. As before, there is one distinctive feature: Utility promises go on or below the 45 degree line for some w^*. This implies that it is too costly to make agent 1 work when his utility promise is above w^*. In that region of utility promises, the effort of agent 1 switches to the lowest level possible. This is the result of our particular double-sided model and is not present in a general principal-agent model. However, there is a similarity in that leisure is a normal good, and thus increases with utility promises.

1.8.2.4 Invariant Distributions and Effort Transitions

Figure 1.14 displays the invariant distributions of utility promises and efforts, while Figure 1.15 shows the steady-state distributions of consumption and aggregate output. The long-run predictions of the ex-post model with private information are similar to the ones with ex-ante limited commitment model with private information. While the invariant distribution of utility promises in the ex-post commitment model

Figure 1.13: Utility Promises and Efforts in Ex-Post Limited Commitment and Private Information Models



converges to some absorbing state, the invariant distribution in a model with private information has more absorbing states. These implies that in the steady-state the utility promises fluctuate within the bounds identified by the probability distribution.

Similarly, we observe the difference in the optimal recommendations for efforts. In the full information ex-post limited commitment model, agent 1 always exerts higher effort and is poorer (his distribution is more to the left in the top row) in terms of steady-state utility promise, while agent 2 is exerting lower effort and is richer in terms of life-time utility. That is, we observe "working poor" and rich agents. In contrast, in the model with private information, both agents are recommended to work, and the spread in the steady-state utility promises decreases (agent 1's distribution shifts to the right in top row, and agent 2's distribution shifts right in the second row). The model society with equal treatment of agents becomes "fairer."

In Figure 1.15 the steady-state distributions of consumption and aggregate output are similar in both full information and private information environments. The difference lies in the expected steady-state consumption and output. In the model with ex-post limited commitment and private information, the expected aggregate output is 3.46, which is lower than 3.59 in the full information version. As said before, some of the potential surplus is lost to provide proper incentives.

Similarly, the transition probability matrices for effort processes are computed for these models and are given in Table 1.4. In the full information limited commitment problem, one of the agents works most of the time, while in the model with private information, both agents work almost equally in a steady-state.

Figure 1.14: Invariant Distributions in Ex-Post (left column) and Ex-Post Limited Commitment with Private Information (right column) Models: Utility Promises (top two rows) and Effort (bottom two rows). The red line denotes the autarky

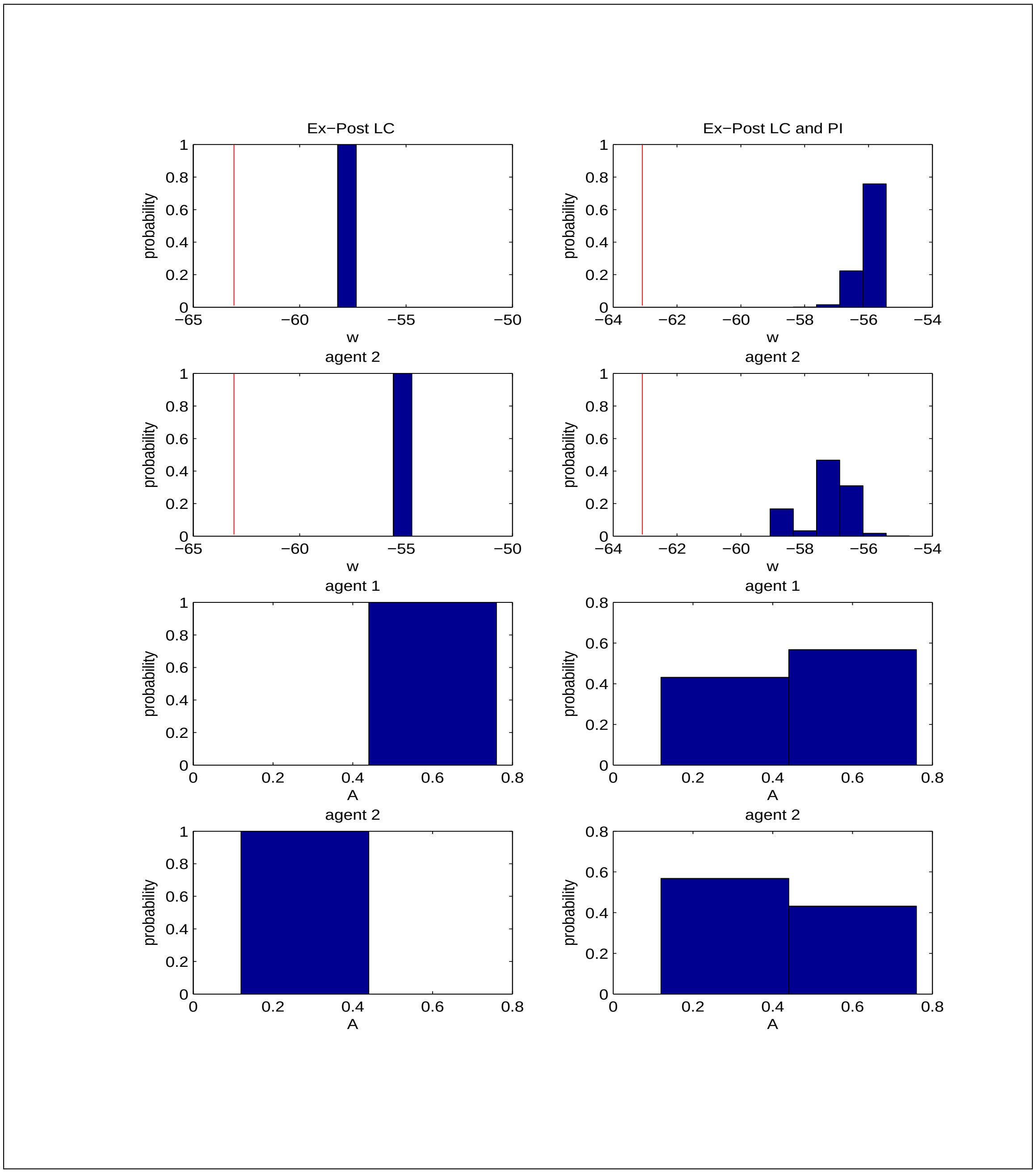


Figure 1.15: Invariant Distributions in Ex-Post (left column) and Ex-Post Limited Commitment with Private Information (right column) Models: Consumption (top two rows) and Aggregate Output (bottom row)

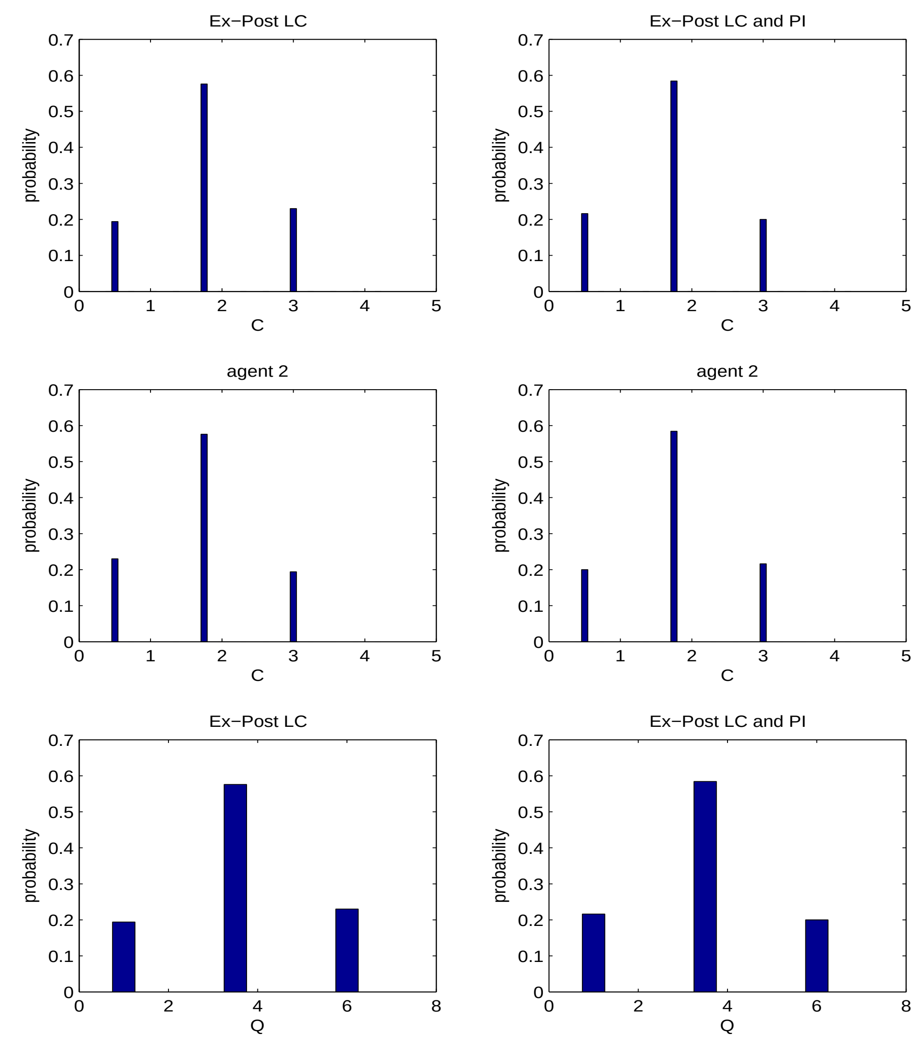


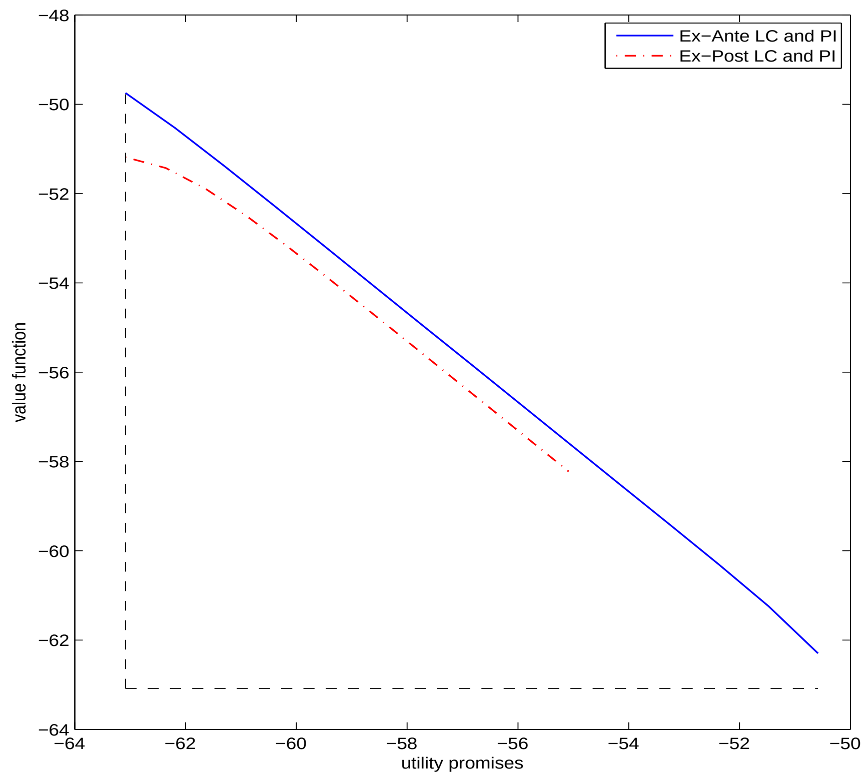
Table 1.4: Transition Probability Matrix: Effort Levels of Agent 1. Ex-Post (upper panel) and Ex-Post with Private Information (lower panel) Limited Commitment Models

Ex-Post LC	$s_{t+1} = a^L$	$s_{t+1} = a^H$
$s_t = a^L$	0.91	0.09
$s_t = a^H$	0	1
	Steady-State Probability Matrix	
	0	1
Ex-Post LC and PI	$s_{t+1} = a^L$	$s_{t+1} = a^H$
$s_t = a^L$	0.35	0.65
$s_t = a^H$	0.46	0.54
	Steady-State Probability Matrix	
	0.42	0.58

1.8.3 Ex-Ante vs. Ex-Post Commitment with Moral Hazard

The predictions of the model with ex-ante limited commitment with private information and the ex-post limited commitment model with private information are very similar. Figures 1.16-1.19 compare the two models. Figure 1.16 compares the value functions of the limited commitment models with private information. The vertical (horizontal) dashed black lines shows the autarky value U_{aut} for agent 1 (agent 2). The value function of the ex-ante commitment problem is higher than the one with ex-post limited commitment because the ex-post limited commitment constraints are tighter. The consumption and utility promises patterns are similar in both models as evident from Figures 1.17 and 1.18. The prediction of the model with ex-post limited commitment and private information are very similar to the predictions of the model

Figure 1.16: Value Functions in Ex-Ante and Ex-Post Limited Commitment with Private Information Models. The vertical (horizontal) dashed black line shows the autarky value U_{aut} for agent 1 (agent 2)



with ex-ante limited commitment and private information. The difference is that in the former model, optimal consumption varies in more states near the bounds. The patterns of the optimal utility promises resemble the predictions of a standard principal agent model with rewards being associated with higher outputs and vice versa.

The invariant distributions of utility promises, efforts, consumptions, and aggregate output are shown in Figures 1.19 and 1.20. Both types of models predict the invariant distributions of utility promises, with mass around the middle of the utility promise space (top two rows in Figure 1.19). The distributions have absorbing states, but the distributions are not completely degenerate. This is the result of the interplay between lower (upper) bounds on punishments (rewards) and the incentive compatibility required by the optimal contract. The variability in utility promises is needed to provide correct incentives for effort. In a standard principal-agent model with no bounds on utility promises, the punishments can be made arbitrarily severe and the agent's current utility promise can be driven to infinitely small number. This makes it less costly for the principal to provide the spread in future utility promises. Such a scenario is not possible in our model because the bounds on utility promises act as "reflecting barriers" and push the agents out of the lower bounds.

The absence of "immiserization" effect is similar to the findings of Atkeson and Lucas (1995). In our models, as well as in Atkeson and Lucas (1995), the lower and upper bounds are "reflecting barriers." It is enough to receive one high (low) output realization on the lower (upper) bound to be pushed back inside the bounds.

Figure 1.17: Consumption in Ex-Ante and Ex-Post Limited Commitment with Private Information Models

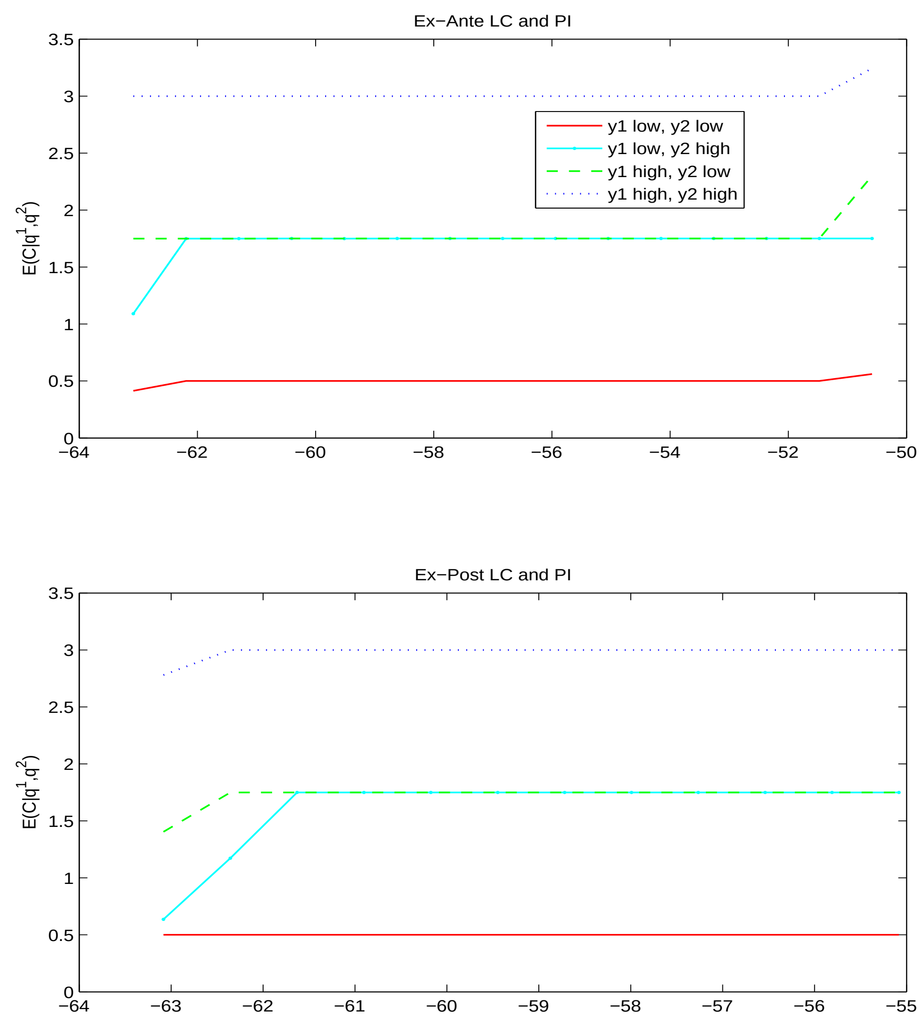
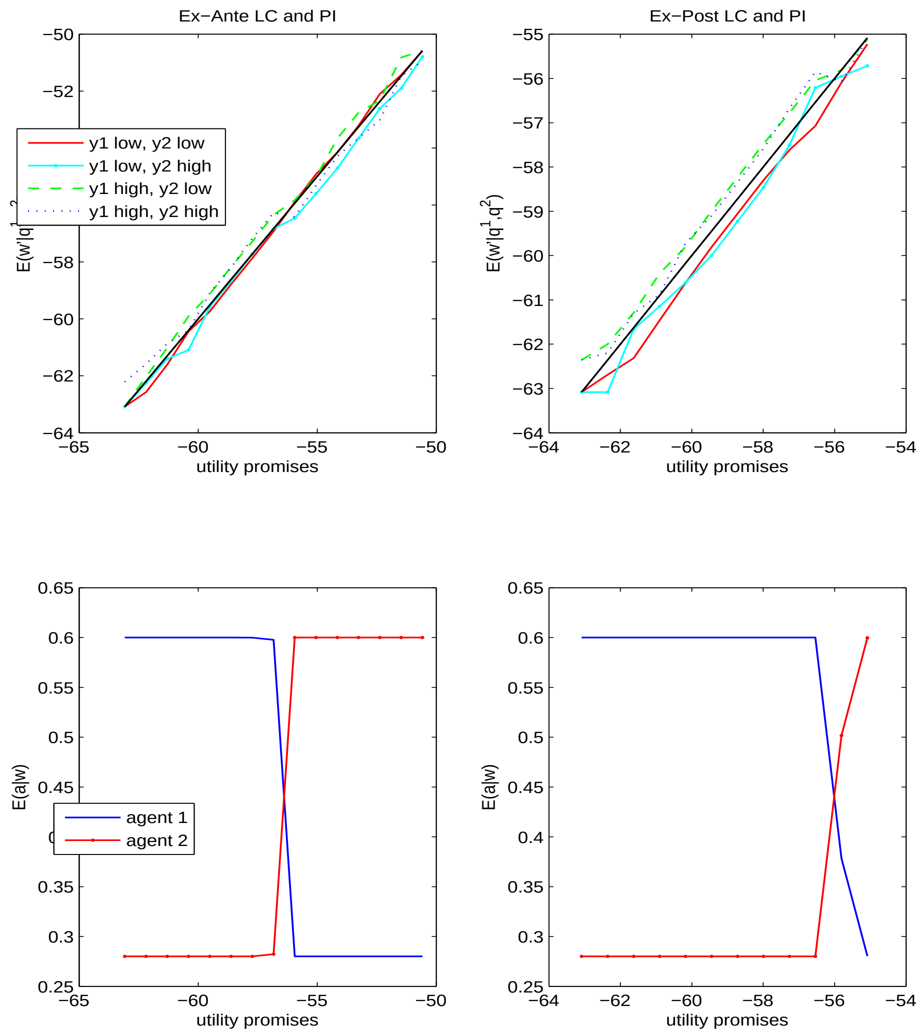


Figure 1.18: Utility Promises and Efforts in Ex-Ante and Ex-Post Limited Commitment with Private Information Models



In fact, the policy functions for future utility promises in our models resemble those in Atkeson and Lucas (1995), and that is why we get similar results.

The transition probabilities for the agents' effort processes are given in Table 1.5. In the current parameterization, agent 1 in ex-post limited commitment model with private information exerts higher effort more often that agent 1 in the ex-ante limited commitment model with private information.

Table 1.5: Transition Probability Matrix: Effort Levels of Agent 1. Ex-Ante (upper panel) and Ex-Post (lower panel) Limited Commitment with Private Information Models

Ex-Ante LC and PI	$s_{t+1} = a^L$	$s_{t+1} = a^H$
$s_t = a^L$	0.49	0.51
$s_t = a^H$	0.71	0.29
	Steady-State Probability Matrix	
	0.58	0.42
Ex-Post LC and PI	$s_{t+1} = a^L$	$s_{t+1} = a^H$
$s_t = a^L$	0.35	0.65
$s_t = a^H$	0.46	0.54
	Steady-State Probability Matrix	
	0.42	0.58

1.9 Concluding Remarks

The dynamic contract models of private information are known to produce a degenerate steady-state distribution of consumption and utility promises, with the agent's utility becoming arbitrarily small with probability one. In this paper we

Figure 1.19: Invariant Distributions in Ex-Ante (left column) and Ex-Post (right column) Limited Commitment Models with Private Information: Utility Promises (top two rows) and Effort (bottom two rows). The red line denotes the autarky

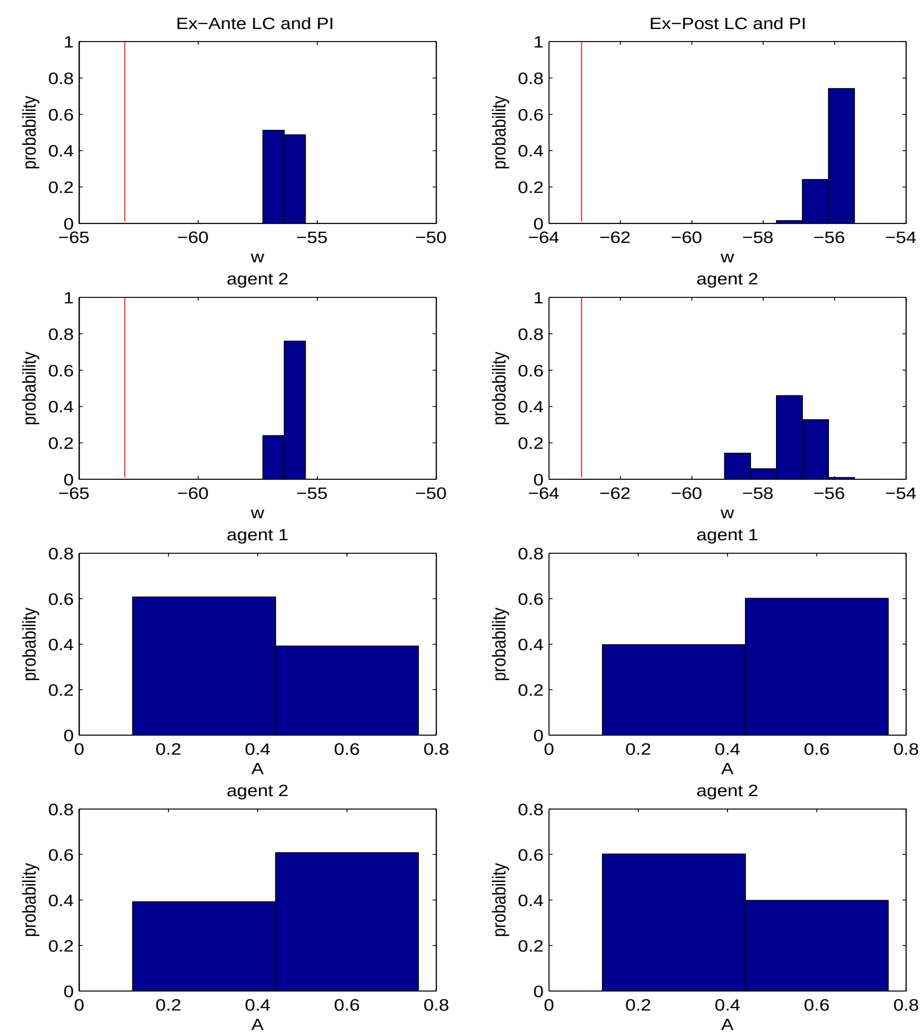
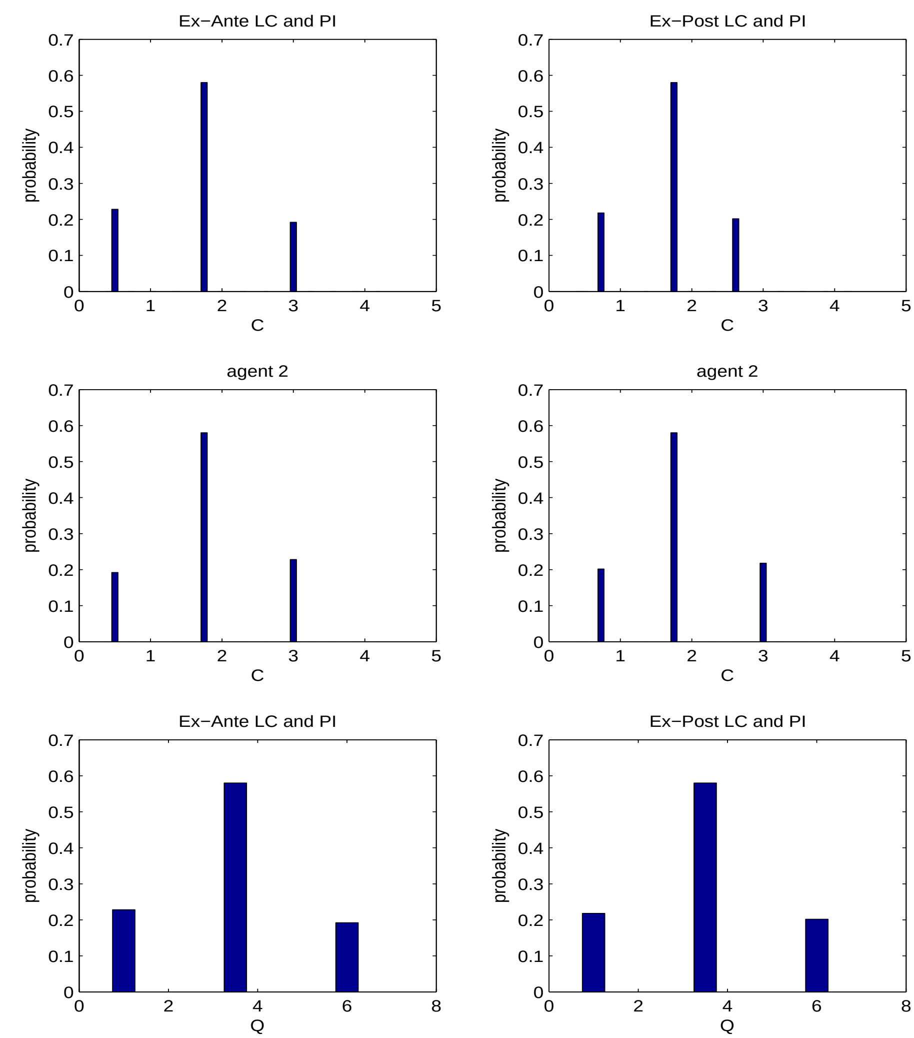


Figure 1.20: Invariant Distributions in Ex-Ante (left column) and Ex-Post (right column) Limited Commitment Models with Private Information: Consumption (top two rows) and Aggregate Output (bottom row)



explore the steady-state distributions of consumption, efforts, and utility promises in model environments that impose limited enforceability of dynamic contracts, and in effect, create lower bounds on utilities of the agents. To be more precise, the environments include two identical risk-averse agents that exert possibly unobservable efforts to produce individual outputs. The two agents are assumed to enter the risk-sharing arrangement and share the outputs. However, the contracts have to be self-enforcing and provide at least the autarkic value to both agents.

We find that in the long-run, the contracts in such limited commitment environments with and without private information do not exhibit "immiserization" property, with one agent consuming all the output and the other agent consuming nothing. In addition, we do not observe one of the agents being driven to lower bounds in the long-run. Rather, in the steady-state the utility promises cluster around some middle value of utility promises for both agents, and the consumption distribution is clustered around the consumption levels that reflect the equal division of aggregate output.

Comparing limited commitment environments with full and private information, we show that the recommended work patterns significantly differ between them. When the efforts are observable, there is no need to motivate the agents to work through punishments and rewards of future consumption. As a result, the steady-state distribution of utility promises is degenerate and only one of the agents exert high effort in the steady-state. This particular result about the distribution is consistent with Kocherlakota (1996), who shows that if the agents are particularly patient, then the distribution of utility promises is degenerate. In our models, the mass of the distribution is concentrated on some inside value of the utility promise space, and not on the lower bounds (with one agent consuming everything in the long-run).

In the limited commitment environments with private information, the optimal contract has to provide incentives for effort. This leads to a less degenerate steady-state distribution of utility promises. The distribution is clustered around several states inside the bounds. In fact, we find that the expected steady-state utility promises of the agents become closer in value under private information. This implies that in the world in which each agent is treated the same, the introduction of private information (and a need to provide incentives for work) leads to a "fairer" society in which both agents are almost equally likely to exert high effort.

The absence of "immiserization" effect in our private information models is similar to the findings of Atkeson and Lucas (1995). In our models, as well as in Atkeson and Lucas (1995), the lower and upper bounds are "reflecting barriers." It is enough to receive one high (low) output realization on the lower (upper) bound to be pushed back inside the bounds. In fact, the policy functions for future utility promises in our models resemble those in Atkeson and Lucas (1995), and that is why we get similar results.

We also find that optimal contracts in our models show several properties that are present in the literature on limited commitment and moral hazard. Namely, the environment with ex-post limited commitment is more restrictive than the ex-ante limited commitment environment (the limited commitment constraints bind in more states in the former model); the incentive-compatible contracts reward higher outputs and punish lower outputs in some states of the world; the effort levels decrease with utility promises as leisure is a normal good.

In addition, there are several features that are particular to our model. There are some states of the world where the utility promises are not used or are not as effective as rewards and punishments. They are near and on the lower and upper bounds of the utility promise space. For example, unless one of the agents is close to his or her lower or higher bound, the aggregate consumption is split in half independently of output realizations even in the presence of private information. If the agents are near the commitment bounds, then the one closer to the lower bound has to share his or her output with the other agent regardless of output realizations. This is due to the other agent's utility promises hitting the upper bound with no scope for an increase in utility promises. In order to guarantee such high current utility promises to the other agent, the contract increases that agent's consumption in the current period. In contrast, the standard principal-agent model predicts that consumption and utility promises should vary with output realizations, and higher output realizations should be rewarded with higher current consumption and higher future utility promises. Moreover, although optimal utility promises behave according to the standard principal-agent model, there is a certain level of current utility promises such that for states with utility promises above that level, agent 1 stops and agent 2 begins exerting high effort and vice versa.

Finally, we want to contrast the optimal contracts in our environment with optimal relative dynamic contracts. For example, Yeltekin (1997) finds that in the model in which one principal contracts with two agents who exert unobservable efforts to produce individual outputs, the optimal consumption depends on the relative difference in output realizations. Thus, the agent is rewarded with higher consumption and utility promises if his or her output realization is larger than that of the other agent. In our models with private information the opposite happens: Unless the agents are close to their commitment limits, the optimal consumption is equal between the two agents no matter what the output realizations are. Thus, optimal consumption in our environment exhibits tournament-like features of relative contracts only when close to the bounds. In addition, the optimal utility promises reward high outputs and punish low outputs in relative contracts, whereas in our models this happens only within the utility bounds.

To summarize, we show that when there is private information about efforts, the risk-sharing is diminished because optimal consumption has to vary more across states when the agents are constrained. The commitment bounds restrict the rewards and punishments rendering them ineffective near the limits. On the other hand, the presence of private information creates the society of working middle class, as the steady-state distributions of utility promises and efforts are more equal.

CHAPTER 2
THE CAPITAL STRUCTURE AND PERFORMANCE OF BUSINESS START-UPS: THE ROLE OF UNOBSERVED INFORMATION AND INCENTIVES

2.1 Introduction

The question of whether business financing decisions have any effect on a firm's performance and market value is one of the central issues in corporate governance literature (Williamson (1988)). Modigliani and Miller (1958) demonstrated conditions under which capital structure decisions do not affect market value. However, the theoretical literature on informational asymmetries and effects of agency costs on performance is large and growing (Jensen and Meckling (1976)). Economic theory suggests that different capital structures create different incentives for entrepreneurs when their actions (for example, effort) are not perfectly observed. For example, the dilution of an entrepreneur's ownership through outside equity may decrease her incentives to exert effort because she has to share the returns with other stakeholders. Lower effort, in turn, translates into a weaker performance of her firm. While these theories were extensively tested for established publicly traded firms, there are only a few papers that study the capital structure of start-up firms that are not plagued by survivorship bias or limited to certain regions and industries (see, for example, Cassar (2004)).[1] Our primary focus is on small business start-ups in which the potential asymmetric information problems may be especially pronounced because of inherent

[1]Survivorship bias results from the fact that we typically have a non-random sample of all business start-ups because we do not observe the failed ones.

informational opaqueness of firms in their first years of existence.

We contribute to the the growing empirical literature by testing the effects of capital structure on the performance of a sample of small businesses in their first years of existence. In contrast to most of the existing studies (Reid (1999), Majumdar and Chhibber (1999), and Weill (2003), we explicitly recognize potential endogeneity of the capital structure. Endogeneity of capital structure can lead to biased results in a regression explaining performance. The bias results from the fact that capital structure is a choice variable and it can be affected by unobservable business characteristics that could also affect performance.[2] In such cases, the measures of capital structure would be correlated with the error term.

We deal with the issue of potential endogeneity of capital structure by using a type of the endogenous treatment model. In addition to allowing us to obtain unbiased estimates of the incentive effects of capital structure on performance, our estimation framework allows us to quantify the strength of any potential selection effects. We also contribute to the empirical literature by proposing new instruments for the effect of capital structure on performance that are consistent with theories of entrepreneurship and lending. To approximate initial capital structure, we employ three broad measures of outside business financing: bank and government loans, funds supplied by individual investors, and any outside financing whether provided by banks

[2]The examples of such characteristics may be indicators of quality, productivity, or risk properties of a business project that are known only to the entrepreneur (Darrough and Stoughton (1986)). If an entrepreneur expects her business to be very successful in the future, she would prefer to engage debt as opposed to external equity to retain all the residual profits after repaying the loan.

or outside investors.[3] Our performance measures are survival, the growth in number of employees, and total sales per worker.

The primary data source used in this paper is the national survey of business start-up firms called *New Business in America: The Firms and Their Owners*. This survey was first fielded in 1985 by the National Federation of Independent Business (NFIB) Foundation. One of the distinguishing features of our sample is the relatively young age of the surveyed businesses (the average age is just over 14 months). In contrast, Federal Reserve's Surveys of Small Business Finances, often used in research on small non-public companies, contains data on much older firms. For example, the average age of a firm sampled by the National Survey of Small Business Finances (NSSBF) is equal to 13.4 years (Bitler, Moskowitz, and Vissing-Jorgensen (2005)). In this respect, the study that comes closest in terms of the relatively young sample of businesses analyzed is the paper by Reid (1999). Reid (1999) uses a sample of Scottish firms with the average age of 21 months. The paper models the survival probability after one year as a function of different measures of financial structure. The results are generally inconclusive. Access to trade credit and previous bank financing (both as dummy variables) have positive effects on survival probability while presence of any debt or extended purchase commitments (also dummy variables) have a negative effect. The leverage ratio typically employed in the literature on capital structure was found to be not statistically significant. The overall conclusion is that financial factors

[3]For each of these three measures, we calculate two ratios – to the total capital and to the total internal equity capital.

are less important than non-financial factors in determining survival probability.

Our results indicate that controlling for endogeneity of capital structure measures produces qualitatively different results when compared to uncorrected coefficients. This is especially pronounced when performance is measured by the sales per employee. The effects of leverage on the performance measures of business start-ups are mostly insignificant, contrary to previous findings on well-established firms. In contrast, outside equity decreases chances of survival while increasing growth in employment and sales in surviving businesses.

This paper is organized as follows. Section 2.2 provides an extensive literature review on capital structure and business performance theories. Section 2.3 describes our econometric model, identification, and the algorithm used for estimation. Section 2.4 discusses the data. Section 2.5 provides the results and Section 2.6 concludes.

2.2 Literature Review

To evaluate the effect of capital structure on firm survival and growth while controlling for selection, we concentrate on two large theoretical areas – optimal capital structure theories and theories of incentives implied by a given capital structure. Although there are several theories that incorporate both selection and incentive effects, we are not aware of a single unifying theory that explains the problem at hand. While there are many competing finance theories of optimal capital structure, most were developed for large companies with dispersed ownership where the influence of a single manager or owner is likely to be insignificant. In the case of start-up firms, an entrepreneur herself and her incentives are major forces behind the choices and performance of her firm. Furthermore, contract theory suggests several possible effects of capital structure on the entrepreneur's effort and/or her choice of risk-return characteristics of a given project. This section reviews the most significant implications of the relevant theoretical literature.

Given the various predictions provided by the literature on capital structure and performance, we do not have prior expectations about the way unobservable characteristics and capital structure affect performance. Instead, we summarize the literature into three main hypotheses and later discuss the consistency of our results with these hypotheses.

2.2.1 Capital Structure Theories

There are four leading theories of optimal capital structure developed in the finance literature (see Myers (2003) for a comprehensive summary). Here we briefly describe them and concentrate on the ones that seem most relevant for business start-up financing:

1. *The Modigliani-Miller value-irrelevance theory* states that sources of financing do not matter for the value of the firm as long as the capital markets are "perfect." Perfect markets imply that markets for capital are not only competitive and frictionless, they are also complete and it is possible to insure against any possible contingency that may arise. This theory is mainly used as a starting point to identify the situations when markets are incomplete and capital

structure may matter.

2. *The static trade-off theory* implies that firms choose optimal debt-to-equity ratios such that the tax benefits associated with debt are equal to the distress costs associated with extra debt at the margin. Interest tax benefits of debt increase the value of the firm, while too much debt increases risk of bankruptcy or exacerbates agency costs like conflicts between creditors and shareholders. However, there appears to be no definitive research that shows that tax incentives play any significant role in debt policy decisions. Furthermore, empirical research shows that companies do not try to achieve their optimal debt ratios.

3. *The pecking-order theory* incorporates asymmetric information about the firm's assets and growth opportunities. As a result, the value of shares may not reflect the true value of the firm and the issuance of new shares may signal that either those opportunities are good or managers are trying to sell overvalued shares. In equilibrium, this leads to the following capital structure: firms prefer internal to external finance; if external financing is needed, firms first issue less risky debt and only then outside equity. In other words, if the manager of a firm has favorable information about assets and growth opportunities, he will avoid external equity financing (Myers and Majluf (1984)).

4. *Agency and asymmetric information theories of capital structure* pioneered by Jensen and Meckling (1976) state that some unobservable characteristics or actions influence the choice of capital structure. Agency theory recognizes that

the interests of managers and owners in the firm are not aligned. This implies a similar capital structure to pecking-order theory, although the underlining principles are different: pecking-order theory assumes that the interests of managers and outside owners coincide. If the firm starts as being fully owned by the manager, the incentives are aligned properly. If external financing is required, then the firm should turn to debt to maintain proper incentives. Once debt becomes too risky and there is a chance of default, then the firm turns to the last source of additional capital, outside equity.

It is worth emphasizing that these theories were developed to explain financing decisions of big corporations. Among them, the last two theories are most suitable for small and start-up firms because these firms usually are most opaque and do not have an established record. This may explain why the majority of start-up firms do not have any outside financing at all and all the initial investment is financed by the entrepreneur's savings.[4]

We concentrate on several relevant theories that describe the relationship between unobservable characteristics of the entrepreneur (or a firm) and capital structure. Leland and Pyle (1977) and Ross (1977) develop models in which "good" entrepreneurs signal their quality. The paper of Leland and Pyle (1977) assumes that quality of the project is known only to the risk-averse entrepreneur who wants to diversify her risks in the project. They show that if the level of self-financing is

[4]Berger and Udell (2003) show that among small firms sampled in the 1993 National Survey of Small Business Finance, personal and close relatives funds contribute around 45% of all capital employed. In our data set this number is close to 64% (see Table 2.2 below).

observable, then good-quality entrepreneurs would signal their quality by partially financing their projects at the expense of diversification. In Ross (1977) "good" entrepreneurs choose debt because the risk of bankruptcy is lower for them than for "bad" entrepreneurs. Myers and Majluf (1984) argue that if the entrepreneur tries to raise outside equity to finance the project then the value of the project may not be perceived as very high by outsiders since the entrepreneur wants to share its proceeds. Therefore, financial investors would demand a high price for external finance. In that case, debt is preferable to outside equity even though bankruptcy becomes an issue. This leads to the pecking-order theory with internal financing being the cheapest way to finance the business.

All these theories predict that "better" firms would choose debt to signal their quality and that they would prefer debt to outside equity. Therefore, if there were no incentive effects of capital structure, then we would expect to see that debt is positively related to performance of start-ups because intrinsically good firms choose debt and perform well.[5] We summarize the existing capital structure theories in the following hypothesis:

Hypothesis 1: Firms that expect to be more successful would prefer debt to outside equity and we would expect a positive relationship (measured by correlation) between debt and performance measures; and a negative relationship between outside equity and performance measures.

[5]However, Berger and Udell (2003) show that if debt is too large then there would be an adverse effect of debt on performance as the risk of default increases, implying a negative relationship between performance and debt.

2.2.2 Capital Structure and Performance

In this subsection we describe main theoretical and empirical research on the effect of capital structure on performance. In general, these theories are referred to as agency theories, and they assume that there are either effort incentives or risk incentives of capital structure. For example, outside equity – which usually results in lower ownership share of the entrepreneur-manager – may induce the entrepreneur to exert less effort. Moreover, the entrepreneur may choose either riskier projects, or perquisites, or simply withdraw assets from the firm. This problem of providing the correct incentives to insiders has received a lot of consideration since it was first raised by Jensen and Meckling (1976). Harris and Raviv (1991) and Myers (2001) provide surveys of this literature.

The testable implication of this literature is that debt could be used to alleviate such problems and we should observe a positive relationship between debt and performance. Moreover, the risk of default may discipline entrepreneurs because in case of bankruptcy they risk losing their firms (Grossman and Hart (1982)). The following hypothesis summarizes the agency theories of effort incentives of capital structure:

Hypothesis 2: Based on agency theories about effort incentives created by debt, we expect to see a positive relationship between debt and performance measures, and a negative relationship between outside equity and performance.

While negative effects of outside equity on performance are well understood, there may also be negative incentive effects of debt. For example, an entrepreneur who acquired debt financing may shift into riskier projects and increase the riskiness of her firm. Therefore, for risky firms, outside equity may be a good monitoring device and result in a positive relationship between outside equity and performance (Berger and Udell (2003)).[6] In addition, Dybvig and Wang (2002) argue that debt financing may induce an entrepreneur to keep the revenues and default on her debt. Such problems would result in a negative relationship between debt and performance. The following hypothesis summarizes the agency theories of risk incentives of capital structure:

Hypothesis 3: Based on agency theories about risk incentives created by debt, we expect to see a negative relationship between debt and performance measures, and a positive relationship between outside equity and performance.

2.2.3 Models with Both Types of Informational Frictions

There is also a series of papers that incorporate both adverse selection and moral hazard into financing decision. Darrough and Stoughton (1986) developed a model of optimal capital structure under both adverse selection and moral hazard, which shows that inside equity decreases with volatility of returns and the entrepreneur's effort decreases with higher expected marginal productivity when marginal productivity and riskiness of the project are unobservable characteristics of the entrepreneur. This model predicts that more efficient entrepreneurs would choose more debt while entrepreneurs with riskier projects would prefer less debt and more out-

[6]This is one of the rationales for venture capital financing of fast-growing high-tech companies.

side equity, other things equal. However, due to assumptions of their model, it is not possible to determine the effect of effort on performance. Wahrenburg (1996) constructs a principal-agent model of project investment with both adverse selection and so-called “false” moral hazard. He shows that the optimal contract can be implemented in terms of debt and equity payoffs, with higher-ability agents keeping 100% stake in the project and repaying debt to the principal. Bajaj, Chan, and Dasgupta (1998) modify the model of Leland and Pyle (1977) to allow for both adverse selection and moral hazard in business financing with the degree of moral hazard measured as control rights of the entrepreneur. This model explains capital structure and firm performance in terms of exogenous ownership structure. They show that debt increases with ownership because ownership works as a signal of quality, with higher ownership meaning better quality, and that the performance also increases with ownership. Jullien, Salaniè, and Salaniè (2007) construct a model of moral hazard with agents differing in unobservable risk-aversion. They find that more risk-averse entrepreneurs would prefer debt to equity. Moreover, the probability of success of the project increases with inside equity because it stimulates the entrepreneur’s effort. The testable prediction of these models is that debt is positively related to performance and better firms choose debt over equity. Furthermore, the success of the project is also positively related to debt.

There are two other papers that study capital structure choice and firm performance simultaneously as we do here. The most closely related to our work is a study by Dessi and Robertson (2003). They examine the effect of leverage on performance of established U.K. firms while explicitly accounting for endogeneity of capital structure choices. They find that unobserved firm characteristics are important determinants of capital structure and performance. Furthermore, the leverage stops being significant after controlling for capital structure endogeneity, suggesting that debt is chosen optimally according with the static trade-off theory. However, the main purpose of our study is to examine entrepreneurial firms at the time of their creation, and to do so we employ a different methodology and different measures of performance. Berger and di Patti (2006) consider the impact of capital structure on firm performance (measured as profit efficiency) and argue that firm performance influences capital structure because either more efficient firms have lower expected costs of bankruptcy (therefore, they acquire more debt) or more efficient firms want to protect the rents that come from higher profit efficiency and shareholders prefer to hold more equity to avoid liquidation leading to less debt. Our paper differs from Berger and di Patti (2006) in that we use survival and growth as the performance measures, and they are measured after the choice of initial capital structure is made, and therefore they cannot influence the choice of initial capital structure. The simultaneity in our paper comes from the idea that some unobservable variables influence both capital structure and performance. As a result, capital structure endogeneity has to be taken into account when estimating the effect of capital structure on performance. Furthermore, our sample is not limited to one particular industry, unlike Berger and di Patti (2006) paper, which concentrates on banking industry.

2.2.4 Selection and Moral Hazard in Lending and Insurance Markets

The issue of selection and incentive effects is explored in other markets as well. Edelberg (2004) proposes and tests a model of consumer lending that incorporates both adverse selection and moral hazard. Using the data on mortgages and automobile loans from the Survey of Consumer Finances, she shows that consumers self-select into contracts that differ in terms of interest rates and levels of collateral. Moreover, higher levels of collateral induce consumers to exert higher effort to ensure the loans are repayed. Using a data set that describes the Kansas voluntary deposit insurance system for banks during 1910-1920, Wheelock and Kumbhakar (1995) show that riskier banks selected to participate in the insurance system, and banks in the system chose to hold less reserves and became more prone to risk.

There is a stream of papers that separate moral hazard and adverse selection in automobile insurance markets. Under adverse selection, higher-risk agents are more likely to self-select into contracts with more coverage. They are also more likely to have an accident. At the same time, better coverage has the incentive effect – it induces riskier behavior. In both cases, better coverage is positively correlated with probability of an accident. For example, Dionne, Michaud, and Dahchor (2004) find that low-risk individuals self-select into contracts that provide less coverage over time, and this induces them to change their unobservable efforts to reduce claims. Chiappori and Salaniè (2000), however, find no evidence of adverse selection or moral hazard in the French market for automobile insurance. But Abbring, Chiappori, Heckman, and Pinquet (2003) argue that dynamic analysis would be more relevant because previous experience could partially reveal hidden effort.

2.3 The Model

2.3.1 General Outline

Entrepreneurs are assumed to have private information about the expected future outcome of their start-up. The observed capital structure (e.g., the level of external debt) will be affected by this private information. For example, it is often hypothesized in the theoretical literature that businesses with better prospects will choose debt over external equity because debt does not dilute ownership. Conditional on the chosen capital structure, an entrepreneur decides how much effort to supply, which in turn affects performance. For example, high levels of external equity (as opposed to external debt) are generally believed to reduce the effort because the entrepreneur will own just a part of the business. Based on these hypotheses, we expect to have a positive correlation between the level of debt of each individual start-up and its success.

We have two distinct processes that can generate this positive correlation. On the one hand, entrepreneurs who expect to do well may want to have as large an ownership share as possible and not dilute it with external equity by inviting outside investors. If an entrepreneur does not have high expectations for the future payoff (either because the project is expected to generate fairly low returns or the risk is very high), she may prefer to bring in external investors to share the risk. On the other hand, given the chosen capital structure, entrepreneurs with high levels of debt and low levels of external equity will face relatively high incentives to supply more effort than those entrepreneurs with high levels of external equity because their ownership is not diluted (standard moral hazard). Assuming that high levels of effort translate into better performance, we will once again observe positive correlation between debt and success. The direction of the causality is different. In one case, the expectation of success affects the choice of capital structure. In the other case, the capital structure affects incentives, and thus, probability of success.

Each start-up can face different debt (or external equity) contract offers that reflect its observable characteristics. In other words, observably more promising enterprises may be offered more attractive debt contracts, thus making them more likely to increase their debt levels. However, the important feature of the decision-making process is that firms may have the unobserved by the potential lender propensity to perform well, which would obviously influence both the capital structure decision and the resulting performance. This means that estimating the effect of capital structure on performance will generally produce biased estimates because the error term will correlate with observed debt levels.

These unobserved factors can be accounted for in the following econometric specification. With the subscript i denoting an individual start-up, we denote by Y_i^* some continuous measure of its performance and by L_i^* some continuous measure of its capital structure:

$$Y_i^* = x_{1i}\beta_1 + \gamma L_i^* + \eta_{1i}, \tag{2.1}$$

$$L_i^* = x_{2i}\beta_2 + \eta_{2i}, \tag{2.2}$$

where x_{1i} and x_{2i} are $1 \times k1$ and $1 \times k2$ vectors of exogenous variables; β_1 and β_2 are $k1 \times 1$ and $k2 \times 1$ vectors of parameters, γ is a scalar parameter measuring the effect of the endogenous capital structure on performance; and $\eta_i = (\eta_{1i}, \eta_{2i})'$ is the vector of error terms assumed to be normally distributed with zero mean $\mu = (0, 0)'$ and covariance Σ:

$$\Sigma = \begin{pmatrix} \sigma_{11} & \sigma_{12} \\ \sigma_{12} & \sigma_{22} \end{pmatrix}. \tag{2.3}$$

Importantly to our analysis, the error terms of the two equations are allowed to be correlated with each other. This correlation term is designed to capture unobserved private information about the quality of the start-up, which directly influences the outcome Y_i^* and also affects the capital structure (borrowing) decision L_i^* of each firm. Non-zero correlation implies that capital structure is not exogenous to performance. Ignoring this potential correlation between errors and running equation (2.1) alone would produce biased estimates. Later we discuss the results that assume that there is no correlation between errors of the two equations, which is equivalent to estimating them separately.

We use three measures of performance: the survival of business start-ups within three years of the initial interview, the change in the number of employees (the ratio of total employment in the third year to total employment in the first year), and the total sales per employee in the third (final) year of the survey. The first performance measure is dichotomous while the last two are continuous. We use the percentage of the total investment into business coming from loans as our measure of debt and the percentage of the total investment coming from external individual investors and investment companies as our measure of external equity. We also calculate the combined percentage of external financing. Lastly, we employ percentages of debt, outside equity, and total outside financing to inside equity financing.

All our capital structure measures are continuous censored random variables. When using the discrete measure of performance, we have to make certain adjustments to our error covariance matrix, which will have implications for the estimation procedure. In particular, the variance of the error term of the first equation is normalized to 1. We refer to this specification with the normalized variance of the error in the first equation (dichotomous performance measure) as *Specification 1* and to the model with the unrestricted variance (continuous performance measure) as *Specification 2.*

Denoting by Y_i and L_i the observed measures of performance and capital structure, respectively, we have the following system of equations:

$$\begin{aligned} Y_i^* &= x_{1i}\beta_1 + \gamma L_i + \eta_{1i}, \\ L_i^* &= x_{2i}\beta_2 + \eta_{2i}. \end{aligned} \tag{2.4}$$

The latent data Y_i^* and L_i^* are transformed into observed data Y_i and L_i in the following manner for *Specification 1*:

$$Y_i = I\left[Y_i^* \geq 0\right],$$
$$L_i = I\left[L_i^* \geq 0\right] \times L_i^*, \tag{2.5}$$

and for *Specification 2*:

$$Y_i = Y_i^*,$$
$$L_i = I\left[L_i^* \geq 0\right] \times L_i^*. \tag{2.6}$$

where $I\left[.\right]$ is an indicator function taking value 1 if the expression in brackets is true and value 0 otherwise.

The hypotheses formulated in the previous section can be expressed in terms of the parameters of our model as follows:

Hypothesis 1: We expect $\sigma_{12} > 0$ *for outside debt and* $\sigma_{12} < 0$ *for outside equity.*

Hypothesis 2: Based on agency theories about effort incentives created by debt, we expect $\gamma > 0$ *for outside debt and* $\gamma < 0$ *for outside equity.*

Hypothesis 3: Based on agency theories about risk incentives created by debt, we expect $\gamma < 0$ *for outside debt and* $\gamma > 0$ *for outside equity.*

2.3.2 Estimation Details

We use Bayesian estimation procedures to estimate the system of equations (2.4) jointly. The choice of methodology is motivated by the superiority in performance of Bayesian methods over Maximum Simulated Likelihood (MSL) in this type of endogenous treatment models.[7] The basic idea is to obtain the posterior distribution of the parameters of the model. The posterior distribution is proportional to the product of the likelihood of the observed data and prior distribution of the parameters:

$$p\left(parameters|\ data\right) \propto p\left(data|parameters\right) p\left(parameters\right).$$

We use simulation to obtain samples from the posterior distribution of the parameters because it does not have a form of any recognizable distribution. We develop a straightforward Gibbs sampler with data augmentation to simulate draws from the posterior distribution. The data augmentation step draws the values of latent variables Y_i^* and L_i^* conditional on the observed data and the parameters of the model (see Albert and Chib (1993)). The details of the algorithms are provided below. We derive two separate posterior simulators for each of the two specifications because the sets of the parameters to be estimated are different.

We start by deriving the (augmented) likelihood of the latent variables Y_i^* and L_i^*. We stack the two equations in the following manner:

$$\beta = \begin{pmatrix} \beta_1 \\ \gamma \\ \beta_2 \end{pmatrix}_{(k1+k2+1)\times 1}; \qquad X_i = \begin{pmatrix} x_{1i} & L_i & 0_{1\times k2} \\ 0_{1\times k1} & 0 & x_{2i} \end{pmatrix}_{2\times(k1+k2+1)};$$

$$y_i^* = \begin{pmatrix} Y_i^* \\ L_i^* \end{pmatrix}_{2\times 1}; \qquad \eta_i = \begin{pmatrix} \eta_{1i} \\ \eta_{2i} \end{pmatrix}_{2\times 1}.$$

[7]Munkin and Trivedi (2003).

The system can then be expressed as

$$y_i^* = X_i\beta + \eta_i.$$

We then stack all the observations together as

$$y^* = \begin{pmatrix} y_1^* \\ y_2^* \\ \vdots \\ y_n^* \end{pmatrix}_{2n\times 1} ; X = \begin{pmatrix} X_1 \\ X_2 \\ \vdots \\ X_n \end{pmatrix}_{2n\times(k1+k2+1)} ; \eta = \begin{pmatrix} \eta_1 \\ \eta_2 \\ \vdots \\ \eta_n \end{pmatrix}_{2n\times 1},$$

to produce

$$y^* = X\beta + \eta.$$

We can express the covariance matrix for y^* as

$$\Omega = \begin{pmatrix} H^{-1} & 0 & \dots & 0 \\ 0 & H^{-1} & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & H^{-1} \end{pmatrix}_{2n\times 2n} = I_n \otimes H^{-1}, \quad \text{where} \quad H = \Sigma_{2\times 2}^{-1}.$$

Conditional on the parameters of the model, the augmented likelihood can be expressed as:[8]

$$\begin{aligned} p\,(y^*|\beta,\Sigma) &= (2\pi)^{-\frac{2n}{2}}|I_n \otimes H^{-1}|^{-\frac{1}{2}} \exp\,(-\frac{1}{2}(y^* - X\beta)'(I_n \otimes H^{-1})^{-1}(y^* - X\beta)) \\ &\propto |H|^{\frac{n}{2}} \exp\,(-\frac{1}{2}tr[\sum_{i=1}^{n}(y_i^* - X_i\beta)'H(y_i^* - X_i\beta)]). \end{aligned} \tag{2.7}$$

[8]See appendix for details.

For computational simplicity, the latent variables Y_i^* and L_i^* are treated as additional parameters of the model. The appropriate steps are added to our Gibbs sampling algorithm to draw these latent variables conditional on the realized values of the main parameters of the model. The latent data are then integrated out to obtain the posterior distribution of the main parameters. The augmented posterior $p\left(y^*, \beta, \Sigma \right| \, data)$, which also contains the latent data, is proportional to

$$p\left(y^*, \beta, \Sigma \right| \, data) \propto p\left(data|y^*\right) p\left(y^*|\beta, \Sigma\right) p\left(\beta, \Sigma\right),$$

where $p\left(data|y^*\right)$ is the distribution of the observed data conditional on the latent data (this distribution is going to be different for the two specifications we use), $p\left(y^*|\beta, \Sigma\right)$ is the augmented likelihood, and $p\left(\beta, \Sigma\right)$ is the prior distribution of the main parameters.

We specify independent priors for β and H^{-1}. The prior for β is normal and given by:

$$\beta \sim N(\beta_0, V_0). \tag{2.8}$$

The conditional posterior of β can be shown to be also normal:[9]

$$\begin{aligned} \beta|data, H, y_i^* &\sim N\left(\beta_1, V_1\right) \\ V_1 &= (\sum_{i=1}^{n} X_i' H X_i + V_0^{-1})^{-1} \\ \beta_1 &= V_1(\sum_{i=1}^{n} X_i' H y_i^* + V_0^{-1}\beta_0). \end{aligned} \tag{2.9}$$

The prior and the posterior distributions of the precision matrix H depends on what type of dependent variable Y_i we use. We consider two cases.

[9]See appendix for details.

The first case is when Y_i is a continuous random variable. We assume a Wishart prior for the precision matrix H:

$$H \sim W\left(\nu_0, H_0\right). \tag{2.10}$$

It can be shown that the conditional posterior distribution of H is also Wishart:

$$H|data, \beta, y_i^* \sim W\left(\nu_1, H_1\right) \tag{2.11}$$

$$\nu_1 = \nu_0 + n$$

$$H_1 = \left(\sum_{i=1}^{n}(y_i^* - X_i\beta)(y_i^* - X_i\beta)' + H_0^{-1}\right)^{-1}.$$

The other case that we consider is of the binary survival dependent variable Y_i. The approach developed for the continuous dependent variable is not directly applicable here because the variance parameter in binary discrete choice models is not identified. Only the ratio $\frac{\beta_1}{\sigma_{11}^{1/2}}$ is identified. This follows from the fact that we do not observe the underlying latent propensity Y_i^*. Thus, in the case of dichotomous dependent variable we have to work with the following identified covariance matrix:

$$\Sigma = H^{-1} = \begin{pmatrix} 1 & \rho \\ \rho & \sigma_{22} \end{pmatrix} = \begin{pmatrix} 1 & \rho \\ \rho & h^{-1} + \rho^2 \end{pmatrix}. \tag{2.12}$$

The reason to use the parametrization given above is that it allows us to use the properties of the multivariate normal distribution. In particular, $p\left(\eta_i\right) = p\left(\eta_{1i}\right) p\left(\eta_{2i}|\eta_{1i}\right)$. We restrict $\eta_{1i} \sim N\left(0, 1\right)$, while $\eta_{2i}|\eta_{1i} \sim N\left(\rho\eta_{1i}, \sigma_{22} - \rho^2\right)$. Following McCulloch et al. (2000), we specify the following prior

$$p(\rho, h) = p(\rho)\, p(h) \tag{2.13}$$

$$\rho \sim N(\rho_0, V_{\rho 0})$$

$$h \sim G(\nu_0, h_0),$$

where $G(\nu_0, h_0)$ is the gamma distribution with mean h_0 and degrees of freedom ν_0. The likelihood with this new parametrization can be rewritten as:

$$\begin{aligned} p(y^*|\beta, \rho, h) &\propto |H|^{\frac{n}{2}} \exp(-\frac{1}{2} tr[\sum_{i=1}^{n} \eta_i' H \eta_i]) \\ &\propto h^{\frac{n}{2}} \exp(-\frac{1}{2} \sum_{i=1}^{n} (\eta_{1i}^2 \left(1 + h\rho^2\right) - 2\eta_{1i}\eta_{2i} h\rho + \eta_{2i}^2 h)). \end{aligned} \tag{2.14}$$

Observe that given ρ, h, the distribution of H is degenerate.[10] Therefore, the conditional posterior for β is exactly the same. The conditional posteriors of (ρ, h) are given by

$$\rho | data, \beta, h, y_i^* \sim N(\rho_1, V_{\rho 1}) \tag{2.15}$$

$$V_{\rho 1} = (V_{\rho 0}^{-1} + h \sum_{i=1}^{n} \eta_{1i}^2)^{-1}$$

$$\rho_1 = V_{\rho 1}(\rho_0 V_{\rho 0}^{-1} + h \sum_{i=1}^{n} \eta_{1i}\eta_{2i}),$$

and

$$h | data, \beta, \rho \sim G(\nu_1, h_1) \tag{2.16}$$

$$\nu_1 = \nu_0 + n$$

$$h_1 = [\frac{\nu_0}{h_0(\nu_0 + n)} + \frac{\sum_{i=1}^{n} (\eta_{1i}\rho - \eta_{2i})^2}{(\nu_0 + n)}]^{-1}.$$

[10]It can be shown that the transformation from (ρ, h) to H is one-to-one.

We use Gibbs sampling algorithms to successively draw from conditional distributions for parameters of the model β, H and latent indices Y_i^* and L_i^*. We denote the s^{th} realization of variable a by a^s. The total number of draws $S = S_0 + S_1$ will be made with the first S_0 discarded as the burn-in. We use the following algorithm for *Specification 1*:

step 0: Set $(Y_i^*)^0 = Y_i$, $(L_i^*)^0 = L_i$, $\rho^0 = 0$, and $h^0 = 1$ (which corresponds to Σ equal to identity matrix);

step 1: draw β^1 from the distribution given in (2.9) conditional on $(Y_i^*)^0$, $(L_i^*)^0$, ρ^0 and h^0;

step 2: draw the elements of covariance matrix Σ as a block:

draw ρ^1 from distribution given in (2.15) conditional on $(Y_i^*)^0$, $(L_i^*)^0$, β^1 and h^0;

draw h^1 from distribution given in (2.16) conditional on $(Y_i^*)^0$, $(L_i^*)^0$, β^1 and ρ^0;

step 3: draw $(L_i^*)^1$ conditional on $(Y_i^*)^0$, ρ^1, h^1 and β^1 as:

$$(L_i^*)^1 = \begin{cases} L_i & \text{if } L_i \geq 0 \\ \text{draw from normal distribution} & \\ \text{truncated above at 0 with mean equal to} & \\ x_{2i}(\beta_2)^1 + \rho^1[(Y_i^*)^0 - x_{1i}(\beta_1)^1 + \gamma^1 L_i] & \\ \text{and variance equal to}(h^1)^{-1} & \text{if } L_i < 0; \end{cases}$$

step 4: draw $(Y_i^*)^1$ conditional on $(L_i^*)^1$, ρ^1, h^1 and β^1 as:

$$(Y_i^*)^1 = \begin{cases} \text{draw from normal distribution} & \\ \text{truncated below at 0 with mean equal to} & \\ x_{1i}(\beta_1)^1 + \frac{\rho^1}{(\rho^1)^2+(h^1)^{-1}}((L_i^*)^1 - x_{2i}(\beta_2)^1) & \\ \text{and variance equal to} & \\ 1 - \frac{(\rho^1)^2}{(\rho^1)^2+(h^1)^{-1}} & \text{if } Y_i \geq 0 \\ \text{draw from normal distribution} & \\ \text{truncated above at 0 with mean equal to} & \\ x_{1i}(\beta_1)^1 + \frac{\rho^1}{(\rho^1)^2+(h^1)^{-1}}((L_i^*)^1 - x_{2i}(\beta_2)^1) & \\ \text{and variance equal to} & \\ 1 - \frac{(\rho^1)^2}{(\rho^1)^2+(h^1)^{-1}} & \text{if } Y_i < 0 \end{cases}$$

step 5: repeat steps 1-4 S times.

We use the following algorithm for *Specification 2*:

step 0: Set $(L_i^*)^0 = L_i$, $H^0 = I$ (where I is an identity matrix);

step 1: draw β^1 from distribution given in (2.9) conditional on Y_i, $(L_i^*)^0$, H^0;

step 2: draw the precision matrix H^1 from the distribution given in (2.11) conditional on Y_i, $(L_i^*)^0$, β^1, then invert it to obtain $(\Sigma)^1$;

step 3: draw $(L_i^*)^1$ conditional on Y_i, H^1 and β^1 as:

$$(L_i^*)^1 = \begin{cases} L_i & \text{if } L_i \geq 0 \\ \text{draw from normal distribution} & \\ \text{truncated above at 0 with mean equal to} & \\ x_{2i}(\beta_2)^1 + \frac{(\sigma_{12})^1}{(\sigma_{11})^1}[(Y_i^*)^0 - x_{1i}(\beta_1)^1 + \gamma^1 L_i] & \\ \text{and variance equal to} (\sigma_{22})^1 - \frac{(\sigma_{12}^2)^1}{(\sigma_{11})^1} & \text{if } L_i < 0; \end{cases}$$

step 4: repeat steps 1-3 S times.

For each run of *Specification 1* we set $S_0 = 50,000$ and $S_1 = 50,000$. For each run of *Specification 2* we set $S_0 = 10,000$ and $S_1 = 50,000$. The reason for this difference is that our preliminary Monte Carlo tests showed that it takes longer for parameters to converge to their true distribution if the dependent variable in equation 1 is dichotomous (implying the necessity to simulate the underlying latent variable). We specify proper but sufficiently diffuse priors in all cases. For both specifications, the prior distribution of β is given by

$$\beta \sim N(0_{k1+k2+1}, 100 * I_{k1+k2+1}),$$

where $I_{k1+k2+1}$ is the $(k1 + k2 + 1) \times (k1 + k2 + 1)$ identity matrix. We assume the following Wishart prior for the precision matrix H in the *Specification 2*:

$$H \sim W(\begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}, 3).$$

We choose the following priors for ρ and h in the *Specification 1*:

$$\rho \sim N(0, 100)$$

$$h \sim G(2, 5).$$

We performed some diagnostics of the Markov Chains used in this paper. The post-burn-in first-order autocorrelation coefficient for the covariance parameter was about 0.91 and the autocorrelation for γ was around 0.87. Although both of them are fairly high, the large number of post-burn-in replications (50,000) insures that the sampler covers the posterior distribution sufficiently well (it takes less than 50 iterations for the effects of previous shocks to disappear). Gelman-Rubin statistics were 1.021 for γ and 1.011 for the covariance parameter in the *Specification 1*. The values of Gelman-Rubin statistics in the *Specification 2* were 1.005 for γ and 1.01 for the covariance parameter. These were obtained by running the respective Gibbs sampler 50 times with overdispersed starting values of the parameters of the model (10 values were chosen manually to insure that extreme values were covered, the remaining 40 runs were started at values drawn from a normal distribution centered at zero with a very large variance). These values are within the usual 1.2 cut-off value suggesting that the samplers converged well.

2.3.3 Identification

The system of equations (2.1), (2.2) is non-parametrically unidentified. Technically, the identification can be achieved by using a non-linear transformation from L_i^* to L_i, which we do by employing a censored version of the underlying latent index. Nevertheless, it has long been noted in the literature that it is preferable to achieve identification through exclusion restrictions. Finding appropriate instruments for the effect of capital structure on performance, however, has proved to be quite difficult.

As we already mentioned, there are only a few papers recognizing potential endogeneity of capital structure. Bitler, Moskowitz, and Vissing-Jorgensen (2005) use the following to instrument for the effect of capital structure on effort (which is assumed to be related to performance): (1) a dummy for whether the business was inherited or given to the present owner, (2) a dummy for whether the business was started by the present owner. The omitted category in their analysis consists of those entrepreneurs who bought their current business. In addition, Bitler, Moskowitz, and Vissing-Jorgensen (2005) use the initial investment by entrepreneur as an instrument. Since we do not model effort in our specification, we have to justify the use of similar instruments in our model. It is arguable that all three are fairly weak instruments. The way in which the business was acquired may tell a lot about the (latent) type of entrepreneur, which in turn may play an important role in determining whether a start-up will be successful. The size of initial investment can be linked to the perception by the owner of the risk involved, which in turn may affect her effort and, thus, performance. We have data on whether the business start-up was inherited or started up by the entrepreneur herself. We, therefore, include a dummy for whether an entrepreneur started the business herself. The omitted category includes those who inherited their businesses, were brought in by other owners, promoted, or purchased it. We found that the initial capital investment is a very strong predictor of both performance and our measures of capital structure.

We propose several new instruments for the effect of capital structure on performance. These variables are related to the access to credit by small businesses. We argue that the differences in the ability of small businesses to obtain bank loans affect their capital structure decisions. At the same time, access to credit should not affect performance directly.

Our first instrument is the homestead exemption amount (the value of housing equity that a person can keep in case she declares bankruptcy) for the state where the business is located as an instrument in the capital structure equation. Berkowitz and White (2004) study the effect of state bankruptcy laws on small firms' access to credit. They find that in states with high homestead exemptions, small businesses (both non-corporate and incorporated) are more likely to be credit rationed and face higher interest rates. Following Berkowitz and White (2004), for those states with unlimited homestead exemption we assign the highest observed homestead exemption level, and we include a dummy variable taking the value 1 for these states.[11] We also include the Herfindahl index of the concentration of banking industry for the state of each firm's location.[12] This variable measures the competitiveness of the banking industry in each state. In addition to these two supply-side instruments, we

[11]In 1985, the year of the first interview, eight states had unlimited homestead exemption: Arkansas, Florida, Iowa, Kansas, Minnesota, Oklahoma, South Dakota, and Texas. The highest homestead examption was $90,000 in Nevada.

[12]Herfindahl index is calculated as a sum of squared market shares of each institution in the state. Here we have to note that it is possible to define an institution as any type of establishment – branch or main office. Alternatively, we can count each bank holding corporation as an institution. The Federal Deposit Insurance Corporation (FDIC) routinely collects data on all lending institutions (branches and main offices). However, the data on these is only available to us starting from 1992, which is too long of a period after the first interview year, 1985. We do have data on the assets of all banks in 1985 grouped by bank. Therefore, our Herfindahl index is based on assets of each bank and not counting each branch as a separate institution.

include the median debt-to-assets ratio of firms in each industry and state to account for dependence of small firms in each industry on bank loans.[13] This demand-side variable is introduced to control for "standard" leverage levels in each industry/state. Cetorelli and Strahan (2004) use this variable to study the effect of competition in the banking sector on market structure of other sectors. It is, however, possible to argue that different industries in different states may also differ in their inherent ability to survive and succeed. We address this problem by including the change in number of firms in each industry/state from 1985 (year of the first interview) to 1987 (year of the last interview) in the performance equation. This variable should control for the average ability to survive in each industry/state over the sample period.

2.4 Data

The primary data source used in this paper is the national survey of business start-up firms called *New Business in America: The Firms and Their Owners*. This survey was first fielded in 1985 by the National Federation of Independent Business (NFIB). There were two more waves fielded in 1986 and 1987, respectively. The sample is drawn from a national sample of new business owners that were members of the NFIB. Given that there does not exist a benchmark national sample of new businesses, this survey arguably provides close coverage to a nationally representative population of new businesses. Moreover, the characteristics of small businesses based on the NFIB survey closely match other business surveys (that include new and old

[13]We use the first two digits of the Standard Industrial Classification (SIC) code to define industry.

firms).[14] The survey has some very attractive features, which make it particularly suitable for our research. First, it targets new businesses – the majority of the firms in the sample are younger than two years. We restrict our sample to firms that were created since January 1983. The average firm age is just above 14 months. Other major data sets involving small businesses have considerably "older" samples.[15] We hypothesize that in small new businesses the informational problems we study are especially pronounced. In addition, survivorship bias becomes an important consideration in any survey of mature businesses (which survived until the day of the survey). Second, the survey is longitudinal. Although the response rate is greatly reduced by the third (and final) survey year, it still allows us to study the performance of new start-ups within the next three years after the first wave was fielded. Third, the survey collects an array of important information related to the personal characteristics of entrepreneurs themselves. It has been noted in the literature that these characteristics are important in determining both financial structure and performance of business start-ups (Cassar (2004)). Last, the survey contains state and industry identifiers, which allows easy matching to other ancillary data sets. The survey, however, has several drawbacks. Probably the biggest one has to do with the fact that the individual item non-response rate is quite high, which makes it costly for us to include large numbers of controls in our equations. Moreover, it does not contain direct (from balance sheets) measures of leverage and outside financing. In-

[14]Cooper, Dunkelberg, Woo, and Dennis (1990).

[15]The average age of a firm sampled by the National Survey of Small Business Finances (NSSBF) is equal to 13.4 years (Bitler, Moskowitz, and Vissing-Jorgensen (2005)).

stead, we have information on the percentage of total capital invested prior to the first sale coming from different sources, including bank loans and outside investors.

We now describe the ancillary data sets used in this paper. The information on the change of the number of institutions by state/industry over the period 1985-1987 was obtained from the U.S. Census Bureau's County Business Patterns data set.[16] We follow Cooper, Dunkelberg, Woo, and Dennis (1990) to control for general economic activity in the states by including the change in unemployment rates by state over the period 1985-1987 as an additional control variable in the performance equation. The data were obtained from the Bureau of Labor Statistics.[17] The median debt-to-assets ratio in each industry/state were computed using the Federal Reserve's National Survey of Small Business Finances (NSSBF).[18] This data set was collected in 1987. Ideally, we would want to have this information for the year 1985. However, the 1987 wave of this survey is the closest match available. Dependence on external financing is not likely to change very much over the two-year period. The Herfindahl index reflecting the banking concentration in each state was computed using the Report of Condition and Income data available at the Chicago Federal Reserve Bank's website.[19] The data contain information on all banks regulated by the Federal Reserve

[16] The data set itself is also available in easy-to-download electronic form at the University of Virginia Library's web-page: http://fisher.lib.virginia.edu/collections/stats/cbp/state.html.

[17] Available on the web at: http://www.bls.gov/lau/home.htm.

[18] The data set is available on the web at: http://www.federalreserve.gov/pubs/oss/oss3/nssbf87/nssbf87home.html.

[19] http://www.chicagofed.org/economic_research_and_data/commercial_bank_data.cfm

System, FDIC, and the Comptroller of the Currency. The market share of each bank was calculated based on total assets of this bank divided by total assets of all banks in the state. Finally, information on the bankruptcy homestead exemptions that were in effect in 1985 were obtained from Kosel (1985).

It should be noted that despite a significant non-response rate by the third wave of the survey, we have information on which firms survived, which is generally available whether or not the respondent actually supplied information in the third wave (1987).

Thus, we are able to use the full sample when analyzing survival. The sample sizes used to explain change in total employment and sales per worker in the last survey year are substantially smaller. Additionally, we lose a number of observations when evaluating the effects of different forms of outside financing compared to inside equity (because some businesses were started using only outside financing). After deleting all observations with missing data we arrive at the sample size of 2,820 businesses for analysis of survival (the sample size falls to 2,487 for specifications with ratios of outside financing to inside equity). Similarly, we have 1,522 (1,342) businesses in employment change specifications and 1,489 (1,310) businesses in sales per employee specifications. The samples for employment growth and sales per employee specifications include businesses that responded to the respective questions in the third interview and also failed businesses (we assign zero values of employment growth and sales per employee variables to such firms). Tables 2.1 and 2.2 list the variables (most of variables are based on responses in the first interview) used in

Table 2.1: Variable Definitions and Descriptive Statistics

Variable	Description	Mean	St.dev.	Min	Max
outjob4	Devotes full-time to the business: 1-no outside employment, 0-any outside job	0.843	0.364	0	1
start1	Form of entry: 1- started it, 0-took over existing firm	0.659	0.474	0	1
age1	Age when became principal owner/manager	36.08	9.45	0	68
moved1	Moved residence to go into business: 1-moved, 0-didn't move	0.208	0.406	0	1
partners	Number of full-time business partners	0.418	0.796	0	8
managexp	Any supervisory/managerial experience: 1- yes, 0-no	0.782	0.413	0	1
firequit	Was fired/quit without specific plans: 1-yes, 0-no	0.170	0.376	0	1
diffprod	Product is very different from previous job: 1- yes, 0-no	0.376	0.485	0	1
parenown	Parents owned a business: 1- yes, 0-no	0.443	0.497	0	1
educlev	Highest level of education: 1- less high school, 9-advanced degree	4.34	1.72	1	9
totjobs	The total number of full-time jobs held prior to business formation	4.48	4.25	0	99
bs11	Percentage of business strategy "lower prices"	11.82	16.85	0	100
bs21	Percentage of business strategy "better service"	29.55	21.37	0	100
bs61	Percentage of business strategy "target missed/poorly served customers"	7.39	11.87	0	80
opercont	Strongly agree(1) to strongly disagree(5) with "business operating controls in writing"	2.73	1.12	1	5
sex	Owner's sex: 1-female, 0-male	0.196	0.397	0	1
race	Owner's race: 1-racial minority, 0-not a minority	0.058	0.233	0	1
capinv	Total capital invested prior to the first sale, categorical: $1- \leq \$5,000, 8- \geq \$500,000$	3.38	1.70	1	8

Table 2.2: Other Variable Definitions and Descriptive Statistics

Variable	Description	Mean	St.dev.	Min	Max
invest	Percentage of capital from outside investors (not family or friends) and investment companies (/100)	4.70	17.74	0	100
loans	Percentage of capital from bank and government loans (/100)	31.78	38.44	0	100
outside	Percentage of capital from both loans and outside investors (/100)	36.48	39.46	0	100
oddsyr	The self-perceived chances of success, categorical: 0-no chance, 10-certain success	8.15	2.04	0	10
survive	Survived: 1-yes, 0-no	0.783	0.412	0	1
homestead	Homestead exemption in the state, in $1,000	37.10	34.48	0	90
h_unlimited	1-Unlimited homestead exemption, 0-otherwise	0.268	0.443	0	1
unemp_change	Change (difference) in unemployment in state over period 1985 to 1987	-0.736	1.20	-2.6	1.7
HH	Herfindahl index in the state	725.6	697.9	65.8	3243.7
est_change	Change in the number of establishments by state/SIC code from 1985 to 1987	0.101	0.092	-0.388	0.671
debt_2_assets	Median debt-to-assets ratio for the SIC code	0.245	0.099	0.055	0.841
agef	Age of the firm, in months	14.4	6.8	1	29
changemp	Ratio of total employment in the firm in 1987 to total employment in 1985	1.201	6.568	0	176.7
lgl_form1_2	1-if partnership, 0-otherwise (proprietorship – omitted category)	0.113	0.316	0	1
lgl_form1_3	1-if corporation, 0-otherwise (proprietorship – omitted category)	0.320	0.467	0	1
sales-per-emp	Sales per Employee in Year 3 (in thousands)	.083	.511	0	12.92
loans2inside	Ratio of capital from bank and government loans to inside equity	1.665	5.912	0	99.00
invest2inside	Ratio of capital from outside individual investors to inside equity	.157	.985	0	19
outside2inside	Ratio of capital from loans and outside investors to inside equity	1.822	5.972	0	99.00

this study along with a brief description and summary statistics based on the largest available sample.

2.5 Results

Tables 2.3-2.5 summarize our findings. As shown in Table 2.3, none of the capital structure variables affect survival when the capital structure measures are assumed to be exogenous. However, when we control for endogeneity, the outside equity has significant negative effect on the survival probability. One possible explanation of the estimated negative effect is that external equity induces entrepreneurs to exert lower effort, which in turn leads to lower survival chances (Hypothesis 2). Neither debt nor our measure of overall external finance had any statistically significant effect on survival. The results of our employment growth specifications are shown in Table 2.4. The outside equity was estimated to have a positive statistically significant effect on the employment growth. The positive relationship between the outside equity and the employment growth is consistent with Hypothesis 3, which predicts that outside equity is preferred to debt because it provides better risk incentives and monitoring. Outside equity financing does not have any effect on employment growth if we do not control for endogeneity of financial structure. In contrast, the effects of debt and total outside financing disappear when we control for endogeneity. This is consistent with the findings of Dessi and Robertson (2003). They show that after accounting for capital structure endogeneity, debt does not affect the performance. They suggest that this is consistent with the trade-off theory of capital structure: If the level of

Table 2.3: Model I Results Summary: Survival

	Treatment Coefficient	
Capital Structure Measures	Exogenous	Endogenous
Loans	0.030	-0.054
	(0.074)	(0.182)
Outside Equity	-0.183	-0.957 ***
	(0.156)	(0.356)
External Finance	-0.011	-0.054
	(0.072)	(0.272)
Loans/Inside Equity	0.005	0.001
	(0.006)	(0.010)
Outside Equity/Inside Equity	-0.009	-0.050
	(0.029)	(0.043)
External Finance/Inside Equity	0.004	-0.001
	(0.005)	(0.010)

Note: The sample size is 2,820 for the first three capital structure measures and 2,487 for the last three. Standard errors are displayed in parentheses below coefficients; *** - significant at 1%, ** - significant at 5%.

debt is chosen optimally it should not influence the performance.

The selection effect of outside equity was also statistically significant. Firms with better growth expectations had significantly lower proportions of outside equity to initial capital investments. This result is consistent with Hypothesis 1. Successful entrepreneurs are less willing to share their returns with outside investors and prefer less outside equity in their businesses. The results of our sales per employee specifications are shown in Table 2.5. Neither of our capital structure measures had any effect on this measure of performance without controlling for endogeneity of financing decisions. However, all six financial structure variables have positive and statistically

Table 2.4: Model II Results Summary: Change in Employment

Capital Structure Measures	Treatment Coefficient Exogenous	Endogenous
Loans	1.636 ***	1.560
	(0.609)	(1.021)
Outside Equity	-0.842	10.356 ***
	(1.248)	(0.704)
External Finance	1.352 **	1.297
	(0.590)	(1.057)
Loans/Inside Equity	0.193 ***	0.183 ***
	(0.036)	(0.052)
Outside Equity/Inside Equity	-0.090	1.728 ***
	(0.180)	(0.122)
External Finance/Inside Equity	0.185 ***	0.183 ***
	(0.035)	(0.054)

Note: The sample size is 1,522 for the first three capital structure measures and 1,342 for the last three. Standard errors are displayed in parentheses below coefficients; *** - significant at 1%, ** - significant at 5%.

significant effects on sales when we allow for endogeneity.

When we use the various ratios of outside financing to inside financing, we find that the positive relationship between the performance and those measures of capital structure run contrary to the predictions of private information models. These models imply that the higher the proportion of inside capital, the more aligned are the incentives for the owner. This should lead to a greater performance. However, the results in Tables 2.4 and 2.5 suggest the opposite. The results signify that the young firms experience capital constraints. The firms that have access to outside financing relax these constraints. That is why we observe that firms with outside financing are more likely to expand in terms of employment and have higher sales per employee (which approximates marginal product of labor). The consistent result emerging

Table 2.5: Model III Results Summary: Sales/Employee

	Treatment Coefficient	
Capital Structure Measures	Exogenous	Endogenous
Loans	-0.057	1.387 ***
	(0.049)	(0.056)
Outside Equity	-0.025	1.148 ***
	(0.109)	(0.077)
External Finance	-0.059	1.451 ***
	(0.048)	(0.056)
Loans/Inside Equity	-0.002	0.075 ***
	(0.003)	(0.004)
Outside Equity/Inside Equity	-0.002	0.142 ***
	(0.015)	(0.012)
External Finance/Inside Equity	-0.002	0.084 ***
	(0.003)	(0.004)

Note: The sample size is 1,489 for the first three capital structure measures and 1,310 for the last three. Standard errors are displayed in parentheses below coefficients; *** - significant at 1%, ** - significant at 5%.

from Tables 2.3-2.5 is that outside equity has both selection and incentive effects on performance of business start-ups. At the same time the results differ depending on which performance measure we use. It is possible to speculate that risk-sharing and profit-sharing concerns induce entrepreneurs to select different optimal capital structures. It may be that entrepreneurs care more about outside equity when it comes to survival as opposed to growth. This might explain why many new firms first acquire outside equity and later shift into debt financing.

Our results also suggest that private information about survival chances plays an important role in the outside equity decisions. Business start-ups with higher survival chances had higher levels of outside equity financing relative to the overall amount of capital invested. This result is not consistent with Hypothesis 1, which predicts that firms with better prospects would prefer outside debt because it does not dilute ownership. This suggests that outside investors might be able to more successfully overcome informational problems associated with business start-ups. At the same time, it is likely that survival is a crude measure of performance, which does not properly capture the underlying propensity for long-term success.

There is very little theoretical research dealing with incentive structures facing business start-ups as opposed to large publicly traded firms. This study suggests directions for future research needed to fully understand the differences among various measures of performance and how they are influenced by capital structure choices in entrepreneurial firms. In particular, it is necessary to explicitly differentiate between risk-sharing and profit-sharing incentives of entrepreneurs. Given the nature of small business start-ups, which rarely rely on any outside capital, more work is needed to differentiate between questions related to whether to use any outside capital versus questions related to what kind of outside capital to use.

2.6 Concluding Remarks

This paper is the first to examine the relationship between capital structure and performance of new business start-ups in the presence of imperfect information. We explicitly control for endogeneity when estimating the effects of capital structure on performance. We find that controlling for endogeneity leads to qualitatively different results.

Our results suggest that debt has an effect only on some measures of performance of business start-ups. In contrast, both selection and incentive effects are present in the case of outside equity, indicating that outside investors are able to both overcome informational asymmetries associated with business start-ups and provide better incentives for performance.

Our results differ depending on which measure of performance we use. In particular, we find that firms with higher levels of external financing tend to experience higher employment growth and sales per employee. This finding is inconsistent with the theoretical predictions from asymmetric information models. Our results suggest that most of the the young firms experience significant capital constraints. The firms that have access to outside financing (and are able to relax these constraints) are more likely to expand in terms of employment and have higher sales per employee. These findings also suggest that providers of external finances have more experience with picking the firms that are likely to perform well. As a result, the firms with more outside finance also tend to perform better.

APPENDIX

POSTERIOR DISTRIBUTIONS

Conditional on the parameters of the model, the likelihood can be expressed as:

$$
\begin{aligned}
p\,(y|\beta,\Omega) &= (2\pi)^{-\frac{2n}{2}}|I_n \otimes H^{-1}|^{-\frac{1}{2}}\exp\,(-\frac{1}{2}(y-X\beta)'(I_n\otimes H^{-1})^{-1}(y-X\beta)) \\
&\propto (|I_n|^2|H^{-1}|^n)^{-\frac{1}{2}}\exp\,(-\frac{1}{2}(y-X\beta)'(I_n\otimes H)(y-X\beta)) \\
&\propto |H|^{\frac{n}{2}}\exp\,(-\frac{1}{2}\sum_{i=1}^{n}\eta_i' H\eta_i) \\
&\propto |H|^{\frac{n}{2}}\exp\,(-\frac{1}{2}\sum_{i=1}^{n}(y_i-X_i\beta)'H(y_i-X_i\beta)) \\
&\propto |H|^{\frac{n}{2}}\exp\,(-\frac{1}{2}tr[\sum_{i=1}^{n}(y_i-X_i\beta)'H(y_i-X_i\beta)]).
\end{aligned}
$$

Since we specify the independent priors for β and H^{-1}, the conditional posterior for β is proportional to:

$$
\begin{aligned}
p\left(\beta|data,H^{-1}\right) &\propto \exp\,(-\frac{1}{2}[\sum_{i=1}^{n}(y_i-X_i\beta)'H(y_i-X_i\beta)+(\beta-\beta_0)'V_0^{-1}(\beta-\beta_0)]) \\
&\propto \exp\,(-\frac{1}{2}[\sum_{i=1}^{n}(y_i'Hy_i-2\beta'X_i'Hy_i+\beta'X_i'HX_i\beta) \\
&\qquad +(\beta'V_0^{-1}\beta-2\beta'V_0^{-1}\beta_0+\beta_0'V_0^{-1}\beta_0)]) \\
&\propto \exp\,(-\frac{1}{2}[\beta'(\sum_{i=1}^{n}X_i'HX_i+V_0^{-1})\beta-2\beta'(\sum_{i=1}^{n}X_i'Hy_i+V_0^{-1}\beta_0)]) \\
&\propto \exp\,(-\frac{1}{2}[\beta'V_1^{-1}\beta-2\beta'V_1^{-1}\beta_1]) \\
&\propto \exp\,(-\frac{1}{2}[\beta'V_1^{-1}\beta-2\beta'V_1^{-1}\beta_1+\beta_1'V_1^{-1}\beta_1-\beta_1'V_1^{-1}\beta_1]) \\
&\propto \exp\,(-\frac{1}{2}[(\beta-\beta_1)'V_1^{-1}(\beta-\beta_1)]).
\end{aligned}
$$

The conditional posterior distribution of β is also normal:

$$
\begin{aligned}
p\,(\beta|data, H) &= N\,(\beta_1, V_1)\\
V_1 &= (\sum_{i=1}^{n} X_i' H X_i + V_0^{-1})^{-1}\\
\beta_1 &= V_1(\sum_{i=1}^{n} X_i' H y_i + V_0^{-1}\beta_0).
\end{aligned}
$$

When deriving the posterior of H^{-1}, we first consider continuous Y_i. Independence of prior distributions leads to the following conditional posterior distribution of H:

$$
\begin{aligned}
p\,(H) \propto\ & |H|^{\frac{n}{2}} \exp\,(-\frac{1}{2} tr[\sum_{i=1}^{n} (y_i - X_i\beta)' H (y_i - X_i\beta)]) \times\\
& |H|^{\frac{\nu_0 - 2 - 1}{2}} \exp\,(-\frac{1}{2} tr(H_0^{-1} H))\\
\propto\ & |H|^{\frac{\nu_0 - n - 2 - 1}{2}} \exp\,(-\frac{1}{2} tr[\sum_{i=1}^{n} (y_i - X_i\beta)(y_i - X_i\beta)' H + H_0^{-1} H]).
\end{aligned}
$$

Therefore, the conditional posterior distribution of H is also Wishart:

$$
\begin{aligned}
p\,(H|data, \beta) &= W\,(\nu_1, H_1)\\
\nu_1 &= \nu_0 + n\\
H_1 &= \left(\sum_{i=1}^{n} (y_i - X_i\beta)(y_i - X_i\beta)' + H_0^{-1}\right)^{-1}.
\end{aligned}
$$

The other case that we will consider is of a binary dependent variable Y_i. The conditional posterior of ρ is given by:

$$
\begin{aligned}
p\,(\rho|data,\beta,h) &\propto \exp\,(-\frac{1}{2}\sum_{i=1}^{n}(\eta_{1i}^2 h\rho^2 - 2\eta_{1i}\eta_{2i}h\rho))\exp\,(-\frac{1}{2V_{\rho 0}}(\rho^2 - 2\rho\rho_0)) \\
&\propto \exp\,(-\frac{1}{2}(\rho^2(V_{\rho 0}^{-1} + h\sum_{i=1}^{n}\eta_{1i}^2)) - 2\rho(\rho_0 V_{\rho 0}^{-1} + h\sum_{i=1}^{n}\eta_{1i}\eta_{2i})) \\
&\propto \exp\,(-\frac{1}{2V_{\rho 1}}(\rho - \rho_1)^2).
\end{aligned}
$$

Thus, the conditional posterior of ρ is normal:

$$
\begin{aligned}
p\,(\rho|data,\beta,h) &= N\,(\rho_1, V_{\rho 1}) \\
V_{\rho 1} &= (V_{\rho 0}^{-1} + h\sum_{i=1}^{n}\eta_{1i}^2)^{-1} \\
\rho_1 &= V_{\rho 1}(\rho_0 V_{\rho 0}^{-1} + h\sum_{i=1}^{n}\eta_{1i}\eta_{2i}).
\end{aligned}
$$

The conditional posterior of h is given by:

$$
\begin{aligned}
p\,(h|data,\beta,\rho) &\propto h^{\frac{\nu_0-2}{2}}\exp\,(-\frac{h\nu_0}{2h_0})h^{\frac{n}{2}}\exp\,(-\frac{1}{2}\sum_{i=1}^{n}(\eta_{1i}^2\left(1+h\rho^2\right) - 2\eta_{1i}\eta_{2i}h\rho + \eta_{2i}^2 h)) \\
&\propto h^{\frac{\nu_0+n-2}{2}}\exp\,(-h[\frac{\nu_0}{2h_0} + \frac{1}{2}\sum_{i=1}^{n}(\eta_{1i}^2\rho^2 - 2\eta_{1i}\eta_{2i}\rho + \eta_{2i}^2)]) \\
&\propto h^{\frac{\nu_0+n-2}{2}}\exp\,(-\frac{h(\nu_0+n)}{2}[\frac{\nu_0}{h_0(\nu_0+n)} + \frac{\sum_{i=1}^{n}(\eta_{1i}\rho - \eta_{2i})^2}{(\nu_0+n)}]) \\
&\propto h^{\frac{\nu_1-2}{2}}\exp\,(-\frac{h\nu_1}{2h_1}).
\end{aligned}
$$

Thus, the conditional posterior of h is given by:

$$
\begin{aligned}
p\,(h|data,\beta,\rho) &= G\,(\nu_1, h_1) \\
\nu_1 &= \nu_0 + n \\
h_1 &= [\frac{\nu_0}{h_0(\nu_0+n)} + \frac{\sum_{i=1}^{n}(\eta_{1i}\rho - \eta_{2i})^2}{(\nu_0+n)}]^{-1}.
\end{aligned}
$$

The tables below present the posterior distributions of parameters.The first columns are the parameter names, the second column and third columns are the mean and standard deviations for exogenous capital structure model, and the last four columns are the results for the endogenous capital model.

Table A.1: Model I: Survival - Loans

	Survival		Survival		Loans	
Parameter	Posterior Mean	Posterior Std.	Posterior Mean	Posterior Std.	Posterior Mean	Posterior Std.
$Intercept$	-0.741 ***	0.227	-0.739 ***	0.241	0.061	0.131
$age1$	0.010 ***	0.003	0.010 ***	0.003	-0.006 ***	0.002
$totjobs$	-0.023 ***	0.006	-0.023 ***	0.006	-0.007 *	0.004
$bs11$	-0.004 **	0.002	-0.004 **	0.002	0.000	0.001
$bs21$	0.003 *	0.001	0.003 *	0.001	0.000	0.001
$bs61$	-0.005 **	0.002	-0.005 **	0.002	0.000	0.001
$race$	-0.356 ***	0.108	-0.352 ***	0.108	-0.061	0.064
$outjob4$	0.135 *	0.074	0.134 *	0.074	-0.027	0.040
$unemp-change$	-0.077 ***	0.023	-0.076 ***	0.023		
$est-change$	0.415	0.317	0.419	0.316		
sex	-0.197 ***	0.069	-0.198 ***	0.070	0.137 ***	0.037
$moved1$	-0.001	0.070	0.001	0.072	-0.134 ***	0.037
$partners$	0.032	0.038	0.032	0.037	-0.028	0.020
$managexp$	-0.050	0.069	-0.049	0.070	-0.058	0.036
$firequit$	-0.056	0.073	-0.055	0.073	-0.061	0.040
$diffprod$	-0.266 ***	0.059	-0.264 ***	0.058	-0.017	0.031
$parenown$	0.079	0.056	0.080	0.056	-0.051 *	0.029
$educlev$	0.016	0.017	0.016	0.017	-0.003	0.009
$opercont$	0.075 ***	0.025	0.074 ***	0.025	0.009	0.013
$capinv$	0.055 ***	0.018	0.054 **	0.024	0.132 ***	0.010
$oddsyr$	0.086 ***	0.013	0.086 ***	0.013	0.001	0.007
$agef$	0.009 **	0.004	0.009 **	0.004	0.001	0.002
$lgl-form1-2$	-0.068	0.090	-0.068	0.090	-0.055	0.049
$lgl-form1-3$	-0.072	0.068	-0.070	0.072	-0.198 ***	0.036
$homestead$					-0.003 **	0.001
$h_unlimited$					0.285 ***	0.098
HH					0.000 **	0.000
$debt2assets$					0.014	0.151
$start1$					-0.048	0.031
$Loans$	0.030	0.074	0.048	0.263		
$Sigma$			-0.005	0.073		

Note: The sample size is 2,820; *** - significant at 1%, ** - significant at 5%.

Table A.2: Model I: Survival - Invest

	Survival		Survival		Invest	
Parameter	Posterior Mean	Posterior Std.	Posterior Mean	Posterior Std.	Posterior Mean	Posterior Std.
$Intercept$	-0.715 ***	0.225	-0.662 ***	0.226	-1.706 ***	0.367
$age1$	0.010 ***	0.003	0.010 ***	0.003	-0.003	0.004
$totjobs$	-0.023 ***	0.006	-0.022 ***	0.006	0.011	0.008
$bs11$	-0.004 ***	0.002	-0.004 ***	0.002	-0.005 *	0.002
$bs21$	0.003 *	0.001	0.002 *	0.001	-0.002	0.002
$bs61$	-0.005 **	0.002	-0.005 **	0.002	0.002	0.003
$race$	-0.353 ***	0.108	-0.340 ***	0.107	0.215	0.152
$outjob4$	0.135 *	0.073	0.133 *	0.073	-0.003	0.111
$unemp - change$	-0.076 ***	0.023	-0.075 ***	0.023		
$est - change$	0.407	0.319	0.390	0.314		
sex	-0.198 ***	0.069	-0.204 ***	0.068	-0.177	0.111
$moved1$	-0.003	0.070	0.001	0.070	0.085	0.093
$partners$	0.038	0.038	0.065 *	0.039	0.299 ***	0.042
$managexp$	-0.051	0.069	-0.051	0.068	0.039	0.101
$firequit$	-0.059	0.073	-0.063	0.073	-0.119	0.114
$diffprod$	-0.269 ***	0.058	-0.281 ***	0.058	-0.255 ***	0.088
$parenown$	0.076	0.056	0.068	0.056	-0.157 **	0.078
$educlev$	0.017	0.017	0.016	0.017	0.010	0.023
$opercont$	0.073 ***	0.025	0.067 ***	0.025	-0.083 **	0.035
$capinv$	0.058 ***	0.018	0.064 ***	0.018	0.103 ***	0.024
$oddsyr$	0.086 ***	0.013	0.083 ***	0.013	-0.023	0.019
$agef$	0.009 **	0.004	0.008 *	0.004	-0.008	0.006
$lgl - form1 - 2$	-0.064	0.092	-0.047	0.091	0.400 ***	0.123
$lgl - form1 - 3$	-0.068	0.068	-0.045	0.068	0.433 ***	0.093
$homestead$					-0.001	0.003
$h_unlimited$					0.144	0.253
HH					0.000	0.000
$debt2assets$					0.285	0.384
$start1$					0.159 *	0.086
$Invest$	-0.183	0.156	-0.981 ***	0.342		
$Sigma$			0.303 ***	0.117		

Note: The sample size is 2,820; *** - significant at 1%, ** - significant at 5%.

Table A.3: Model I: Survival - Outside

	Survival		Survival		Outside	
Parameter	Posterior Mean	Posterior Std.	Posterior Mean	Posterior Std.	Posterior Mean	Posterior Std.
$Intercept$	-0.725 ***	0.226	-0.705 ***	0.248	0.164	0.118
$age1$	0.010 ***	0.003	0.010 ***	0.003	-0.005 ***	0.001
$totjobs$	-0.023 ***	0.006	-0.023 ***	0.006	-0.004	0.003
$bs11$	-0.004 **	0.002	-0.004 **	0.002	-0.001	0.001
$bs21$	0.003 *	0.001	0.003 *	0.001	0.000	0.001
$bs61$	-0.005 **	0.002	-0.005 **	0.002	0.000	0.001
$race$	-0.358 ***	0.108	-0.355 ***	0.109	-0.021	0.057
$outjob4$	0.135 *	0.073	0.133 *	0.074	-0.025	0.036
$unemp - change$	-0.076 ***	0.023	-0.075 ***	0.024		
$est - change$	0.410	0.318	0.402	0.315		
sex	-0.194 ***	0.068	-0.191 ***	0.070	0.100 ***	0.034
$moved1$	-0.003	0.070	-0.006	0.072	-0.112 ***	0.033
$partners$	0.033	0.038	0.032	0.038	0.047 ***	0.017
$managexp$	-0.052	0.069	-0.053	0.069	-0.047	0.033
$firequit$	-0.057	0.073	-0.059	0.074	-0.072 **	0.036
$diffprod$	-0.265 ***	0.058	-0.266 ***	0.059	-0.044	0.028
$parenown$	0.078	0.056	0.077	0.057	-0.076 ***	0.026
$educlev$	0.016	0.017	0.016	0.017	-0.002	0.008
$opercont$	0.075 ***	0.025	0.074 ***	0.025	-0.006	0.012
$capinv$	0.058 ***	0.019	0.060 **	0.025	0.128 ***	0.009
$oddsyr$	0.086 ***	0.013	0.086 ***	0.013	-0.002	0.006
$agef$	0.009 **	0.004	0.009 **	0.004	0.000	0.002
$lgl - form1 - 2$	-0.070	0.091	-0.068	0.091	0.006	0.044
$lgl - form1 - 3$	-0.077	0.068	-0.079	0.069	-0.113 ***	0.032
$homestead$					-0.002 **	0.001
$h_unlimited$					0.276 ***	0.088
HH					0.000 *	0.000
$debt2assets$					0.046	0.137
$start1$					-0.022	0.028
$Outside$	-0.011	0.072	-0.051	0.265		
$Sigma$			0.011	0.069		

Note: The sample size is 2,820; *** - significant at 1%, ** - significant at 5%.

Table A.4: Model I: Survival - Loans/Inside

	Survival		Survival		Loans/Inside	
Parameter	Posterior Mean	Posterior Std.	Posterior Mean	Posterior Std.	Posterior Mean	Posterior Std.
$Intercept$	-0.710 ***	0.241	-0.704 ***	0.239	-5.156 **	2.133
$age1$	0.010 ***	0.003	0.010 ***	0.003	-0.091 ***	0.027
$totjobs$	-0.022 ***	0.006	-0.021 ***	0.006	-0.065	0.062
$bs11$	-0.004 **	0.002	-0.004 **	0.002	-0.015	0.015
$bs21$	0.002	0.001	0.002	0.001	0.002	0.012
$bs61$	-0.003	0.002	-0.003	0.002	-0.010	0.022
$race$	-0.343 ***	0.115	-0.343 ***	0.116	-0.070	1.070
$outjob4$	0.139 *	0.078	0.140 *	0.079	0.057	0.676
$unemp-change$	-0.061 **	0.025	-0.061 **	0.025		
$est-change$	0.530	0.340	0.536	0.338		
sex	-0.216 ***	0.074	-0.214 ***	0.074	1.278 **	0.636
$moved1$	0.009	0.074	0.008	0.075	-2.075 ***	0.614
$partners$	0.081 *	0.043	0.082 *	0.042	-0.307	0.336
$managexp$	-0.101	0.075	-0.107	0.075	-1.701 ***	0.594
$firequit$	-0.056	0.077	-0.058	0.078	-1.046	0.674
$diffprod$	-0.242 ***	0.063	-0.242 ***	0.063	-0.075	0.522
$parenown$	0.094	0.060	0.094	0.059	0.032	0.487
$educlev$	0.019	0.018	0.019	0.018	0.000	0.146
$opercont$	0.077 ***	0.027	0.077 ***	0.026	0.104	0.220
$capinv$	0.059 ***	0.020	0.060 ***	0.020	1.870 ***	0.168
$oddsyr$	0.086 ***	0.014	0.086 ***	0.014	0.096	0.121
$agef$	0.009 **	0.004	0.009 **	0.004	0.025	0.036
$lgl-form1-2$	-0.104	0.099	-0.101	0.099	0.158	0.841
$lgl-form1-3$	-0.094	0.072	-0.094	0.072	-2.138 ***	0.598
$homestead$					-0.032	0.020
$h_unlimited$					3.820 **	1.622
HH					0.000	0.000
$debt2assets$					-0.107	2.509
$start1$					-0.215	0.528
$Loans/Inside$	0.005	0.006	0.001	0.010		
$Sigma$			0.280	0.634		

Note: The sample size is 2,487; *** - significant at 1%, ** - significant at 5%.

Table A.5: Model I: Survival - Invest/Inside

	Survival		Survival		Invest/Inside	
Parameter	Posterior Mean	Posterior Std.	Posterior Mean	Posterior Std.	Posterior Mean	Posterior Std.
$Intercept$	-0.705 ***	0.241	-0.688 ***	0.239	-8.928 ***	2.128
$age1$	0.010 ***	0.003	0.010 ***	0.003	-0.018	0.026
$totjobs$	-0.021 ***	0.006	-0.021 ***	0.006	0.061	0.050
$bs11$	-0.004 **	0.002	-0.004 **	0.002	-0.023	0.015
$bs21$	0.002	0.001	0.002	0.001	-0.012	0.012
$bs61$	-0.003	0.002	-0.003	0.002	0.013	0.019
$race$	-0.342 ***	0.116	-0.342 ***	0.116	0.844	0.945
$outjob4$	0.142 *	0.079	0.140 *	0.079	-0.312	0.666
$unemp-change$	-0.061 **	0.025	-0.061 **	0.025		
$est-change$	0.532	0.340	0.530	0.337		
sex	-0.216 ***	0.074	-0.219 ***	0.074	-1.619 **	0.736
$moved1$	0.007	0.075	0.007	0.075	0.384	0.573
$partners$	0.082 *	0.043	0.083 **	0.042	1.484 ***	0.257
$managexp$	-0.108	0.074	-0.110	0.075	-0.037	0.621
$firequit$	-0.058	0.077	-0.059	0.077	-0.250	0.676
$diffprod$	-0.241 ***	0.063	-0.244 ***	0.063	-0.886 *	0.526
$parenown$	0.093	0.060	0.089	0.060	-1.285 ***	0.490
$educlev$	0.019	0.018	0.019	0.018	0.016	0.142
$opercont$	0.077 ***	0.027	0.076 ***	0.027	-0.462 **	0.217
$capinv$	0.062 ***	0.020	0.063 ***	0.019	0.637 ***	0.154
$oddsyr$	0.086 ***	0.014	0.085 ***	0.014	-0.149	0.115
$agef$	0.009 **	0.004	0.009 **	0.004	-0.021	0.035
$lgl-form1-2$	-0.101	0.100	-0.095	0.099	2.002 ***	0.746
$lgl-form1-3$	-0.094	0.072	-0.090	0.072	2.007 ***	0.563
$homestead$					0.002	0.018
$h_unlimited$					-0.166	1.486
HH					0.000	0.000
$debt2assets$					0.489	2.391
$start1$					0.769	0.536
$Invest/Inside$	-0.009	0.029	-0.050	0.043		
$Sigma$			0.636	0.513		

Note: The sample size is 2,487; *** - significant at 1%, ** - significant at 5%.

Table A.6: Model I: Survival - Outside/Inside

	Survival		Survival		Outside/Inside	
Parameter	Posterior Mean	Posterior Std.	Posterior Mean	Posterior Std.	Posterior Mean	Posterior Std.
$Intercept$	-0.712 ***	0.239	-0.707 ***	0.240	-3.655 *	1.949
$age1$	0.010 ***	0.003	0.010 ***	0.003	-0.082 ***	0.025
$totjobs$	-0.021 ***	0.006	-0.021 ***	0.006	-0.029	0.055
$bs11$	-0.004 **	0.002	-0.004 **	0.002	-0.019	0.013
$bs21$	0.002	0.001	0.002	0.001	0.001	0.011
$bs61$	-0.003	0.002	-0.003	0.002	-0.004	0.019
$race$	-0.344 ***	0.117	-0.341 ***	0.116	0.194	0.959
$outjob4$	0.140 *	0.078	0.141 *	0.079	-0.068	0.618
$unemp - change$	-0.061 **	0.025	-0.061 **	0.025		
$est - change$	0.529	0.338	0.540	0.338		
sex	-0.214 ***	0.075	-0.214 ***	0.074	0.866	0.583
$moved1$	0.009	0.075	0.005	0.076	-1.843 ***	0.560
$partners$	0.081 *	0.042	0.081 *	0.043	0.367	0.291
$managexp$	-0.101	0.074	-0.106	0.075	-1.501 ***	0.547
$firequit$	-0.056	0.078	-0.058	0.077	-1.017 *	0.610
$diffprod$	-0.241 ***	0.062	-0.241 ***	0.063	-0.188	0.476
$parenown$	0.094	0.059	0.094	0.059	-0.378	0.447
$educlev$	0.019	0.018	0.019	0.018	-0.009	0.133
$opercont$	0.077 ***	0.027	0.077 ***	0.027	-0.035	0.201
$capinv$	0.059 ***	0.020	0.061 ***	0.020	1.736 ***	0.150
$oddsyr$	0.086 ***	0.014	0.086 ***	0.014	0.057	0.110
$agef$	0.009 **	0.004	0.009 **	0.004	0.014	0.033
$lgl - form1 - 2$	-0.105	0.100	-0.098	0.101	0.894	0.753
$lgl - form1 - 3$	-0.093	0.072	-0.094	0.072	-1.250 **	0.534
$homestead$					-0.025	0.018
$h_unlimited$					3.257 **	1.466
HH					0.000	0.000
$debt2assets$					-0.307	2.322
$start1$					-0.068	0.483
$Outside/Inside$	0.004	0.005	-0.001	0.010		
$Sigma$			0.364	0.618		

Note: The sample size is 2,487; *** - significant at 1%, ** - significant at 5%.

Table A.7: Model II: Changemp - Loans

	Changemp		Changemp		Loans	
Parameter	Posterior Mean	Posterior Std.	Posterior Mean	Posterior Std.	Posterior Mean	Posterior Std.
$Intercept$	-0.459	1.404	-0.452	1.414	-0.440 **	0.188
$age1$	0.006	0.021	0.006	0.020	-0.001	0.002
$totjobs$	-0.016	0.048	-0.016	0.048	-0.010 *	0.006
$bs11$	0.009	0.012	0.008	0.012	-0.001	0.001
$bs21$	-0.009	0.010	-0.009	0.010	0.001	0.001
$bs61$	-0.012	0.016	-0.012	0.016	0.001	0.002
$race$	-0.608	0.763	-0.613	0.759	-0.040	0.089
$outjob4$	0.119	0.507	0.121	0.509	0.056	0.058
$unemp-change$	0.018	0.168	0.019	0.167		
$est-change$	1.043	1.789	1.037	1.785		
sex	-0.495	0.495	-0.488	0.498	0.120 **	0.055
$moved1$	-0.528	0.483	-0.529	0.487	-0.113 **	0.054
$partners$	0.549 **	0.264	0.549 **	0.264	-0.017	0.029
$managexp$	0.320	0.489	0.319	0.491	-0.084	0.053
$firequit$	0.328	0.510	0.330	0.511	-0.020	0.058
$diffprod$	-0.610	0.409	-0.616	0.407	0.001	0.045
$parenown$	0.099	0.386	0.094	0.385	-0.027	0.043
$educlev$	-0.037	0.113	-0.037	0.113	-0.001	0.012
$opercont$	0.140	0.170	0.141	0.170	0.007	0.019
$capinv$	0.009	0.128	0.013	0.136	0.143 ***	0.015
$oddsyr$	0.112	0.092	0.112	0.092	0.007	0.010
$agef$	0.001	0.028	0.001	0.029	0.002	0.003
$lgl-form1-2$	-0.511	0.643	-0.512	0.637	-0.142 *	0.073
$lgl-form1-3$	0.189	0.456	0.181	0.462	-0.215 ***	0.052
$homestead$					-0.003	0.002
$h_unlimited$					0.275 *	0.148
HH					0.000 ***	0.000
$debt2assets$					0.068	0.231
$start1$					0.006	0.046
$Loans$	1.636 ***	0.609	1.560	1.021		
$Sigma$			0.022	0.213		

Note: The sample size is 1,522; *** - significant at 1%, ** - significant at 5%.

Table A.8: Model II: Changemp - Invest

	Changemp		Changemp		Invest	
Parameter	Posterior Mean	Posterior Std.	Posterior Mean	Posterior Std.	Posterior Mean	Posterior Std.
$Intercept$	-0.268	1.407	-1.054	1.423	-1.302 ***	0.483
$age1$	0.004	0.020	0.010	0.021	0.000	0.007
$totjobs$	-0.018	0.048	-0.040	0.049	0.003	0.016
$bs11$	0.008	0.012	0.010	0.012	-0.004	0.004
$bs21$	-0.008	0.010	-0.005	0.010	0.002	0.003
$bs61$	-0.011	0.016	-0.013	0.016	0.007	0.005
$race$	-0.661	0.763	-0.425	0.777	0.089	0.244
$outjob4$	0.150	0.507	0.229	0.521	-0.164	0.159
$unemp - change$	0.016	0.166	-0.045	0.112		
$est - change$	0.776	1.795	0.744	1.220		
sex	-0.416	0.494	-0.313	0.509	-0.153	0.169
$moved1$	-0.580	0.483	-0.719	0.494	0.180	0.149
$partners$	0.551 **	0.265	0.309	0.271	0.078	0.075
$managexp$	0.259	0.487	0.327	0.500	0.040	0.159
$firequit$	0.328	0.513	0.292	0.526	-0.178	0.170
$diffprod$	-0.622	0.411	-0.461	0.420	0.151	0.129
$parenown$	0.061	0.384	0.212	0.395	-0.090	0.120
$educlev$	-0.038	0.113	-0.024	0.116	0.018	0.035
$opercont$	0.142	0.171	0.219	0.175	-0.078	0.054
$capinv$	0.101	0.125	0.013	0.126	0.025	0.038
$oddsyr$	0.114	0.091	0.134	0.094	-0.032	0.029
$agef$	0.004	0.028	0.001	0.029	0.015	0.009
$lgl - form1 - 2$	-0.521	0.642	-1.012	0.655	0.336 *	0.192
$lgl - form1 - 3$	0.091	0.457	-0.169	0.467	0.103	0.142
$homestead$					0.002	0.003
$h_{u}nlimited$					-0.159	0.238
HH					0.000	0.000
$debt2assets$					0.188	0.382
$start1$					0.156 *	0.085
$Invest$	-0.842	1.248	10.356 ***	0.704		
$Sigma$			-12.348 ***	1.327		

Note: The sample size is 1,522; *** - significant at 1%, ** - significant at 5%.

Table A.9: Model II: Changemp - Outside

	Changemp		Changemp		Outside	
Parameter	Posterior Mean	Posterior Std.	Posterior Mean	Posterior Std.	Posterior Mean	Posterior Std.
$Intercept$	-0.522	1.402	-0.522	1.404	-0.302 *	0.169
$age1$	0.006	0.020	0.006	0.020	-0.002	0.002
$totjobs$	-0.019	0.048	-0.019	0.048	-0.003	0.005
$bs11$	0.009	0.012	0.009	0.012	-0.001	0.001
$bs21$	-0.008	0.010	-0.008	0.010	0.001	0.001
$bs61$	-0.012	0.016	-0.012	0.016	0.002	0.002
$race$	-0.590	0.760	-0.587	0.760	-0.074	0.080
$outjob4$	0.132	0.509	0.136	0.509	0.027	0.052
$unemp-change$	0.016	0.167	0.016	0.168		
$est-change$	0.990	1.793	0.993	1.793		
sex	-0.468	0.492	-0.462	0.498	0.085 *	0.050
$moved1$	-0.556	0.481	-0.558	0.482	-0.071	0.048
$partners$	0.518 *	0.265	0.518 *	0.265	0.035	0.026
$managexp$	0.318	0.486	0.315	0.489	-0.074	0.049
$firequit$	0.327	0.515	0.325	0.511	-0.017	0.052
$diffprod$	-0.596	0.407	-0.592	0.411	-0.018	0.041
$parenown$	0.110	0.387	0.112	0.385	-0.057	0.039
$educlev$	-0.035	0.113	-0.036	0.113	-0.003	0.011
$opercont$	0.152	0.170	0.151	0.170	-0.010	0.017
$capinv$	0.015	0.128	0.017	0.141	0.140 ***	0.013
$oddsyr$	0.115	0.092	0.115	0.092	0.001	0.009
$agef$	0.001	0.028	0.001	0.028	0.003	0.003
$lgl-form1-2$	-0.583	0.640	-0.574	0.638	-0.020	0.065
$lgl-form1-3$	0.132	0.458	0.136	0.461	-0.136 ***	0.046
$homestead$					-0.002	0.002
$h_unlimited$					0.235 *	0.134
HH					0.000 **	0.000
$debt2assets$					0.164	0.210
$start1$					0.046	0.042
$Outside$	1.352 **	0.590	1.297	1.057		
$Sigma$			0.013	0.211		

Note: The sample size is 1,522; *** - significant at 1%, ** - significant at 5%.

Table A.10: Model II: Changemp - Loans/Inside

	Changemp		Changemp		Loans/Inside	
Parameter	Posterior Mean	Posterior Std.	Posterior Mean	Posterior Std.	Posterior Mean	Posterior Std.
$Intercept$	-0.236	1.398	-0.210	1.400	-5.347 ***	2.015
$age1$	0.007	0.020	0.007	0.020	-0.038	0.033
$totjobs$	-0.020	0.047	-0.020	0.047	-0.130	0.087
$bs11$	0.010	0.011	0.010	0.011	-0.020	0.018
$bs21$	-0.009	0.009	-0.009	0.010	0.008	0.015
$bs61$	-0.012	0.016	-0.012	0.016	0.003	0.026
$race$	-0.588	0.753	-0.595	0.758	-0.737	1.207
$outjob4$	0.117	0.505	0.119	0.504	0.333	0.803
$unemp-change$	0.019	0.166	0.020	0.165		
$est-change$	0.764	1.785	0.775	1.785		
sex	-0.448	0.491	-0.449	0.492	0.828	0.770
$moved1$	-0.454	0.479	-0.456	0.481	-1.927 **	0.767
$partners$	0.548 **	0.263	0.548 **	0.262	-0.237	0.416
$managexp$	0.416	0.488	0.408	0.485	-1.686 **	0.749
$firequit$	0.313	0.509	0.312	0.507	-0.206	0.821
$diffprod$	-0.613	0.406	-0.619	0.406	-0.072	0.645
$parenown$	0.042	0.381	0.041	0.382	0.031	0.604
$educlev$	-0.048	0.112	-0.049	0.112	-0.002	0.179
$opercont$	0.108	0.170	0.109	0.169	0.177	0.268
$capinv$	0.052	0.123	0.054	0.124	1.442 ***	0.208
$oddsyr$	0.093	0.091	0.092	0.091	0.142	0.146
$agef$	0.001	0.028	0.001	0.028	0.015	0.046
$lgl-form1-2$	-0.807	0.638	-0.793	0.635	0.270	1.003
$lgl-form1-3$	0.111	0.449	0.109	0.449	-2.027 ***	0.727
$homestead$					-0.014	0.023
$h_unlimited$					1.325	1.781
HH					-0.001 ***	0.000
$debt2assets$					0.244	2.289
$start1$					-0.321	0.649
$Loans/Inside$	0.193 ***	0.036	0.183 ***	0.052		
$Sigma$			0.787	2.583		

Note: The sample size is 1,342; *** - significant at 1%, ** - significant at 5%.

Table A.11: Model II: Changemp - Invest/Inside

	Changemp		Changemp		Invest/Inside	
Parameter	Posterior Mean	Posterior Std.	Posterior Mean	Posterior Std.	Posterior Mean	Posterior Std.
$Intercept$	-0.271	1.411	-1.573	1.375	-2.538 **	1.260
$age1$	0.004	0.021	0.017	0.021	-0.011	0.019
$totjobs$	-0.020	0.048	-0.028	0.049	0.032	0.042
$bs11$	0.008	0.012	0.007	0.012	-0.014	0.011
$bs21$	-0.008	0.010	-0.007	0.010	0.003	0.009
$bs61$	-0.011	0.016	-0.011	0.017	0.019	0.014
$race$	-0.663	0.759	-0.376	0.773	-0.011	0.693
$outjob4$	0.156	0.509	0.176	0.520	-0.550	0.455
$unemp - change$	0.015	0.168	-0.036	0.101		
$est - change$	0.788	1.786	0.493	1.100		
sex	-0.419	0.498	-0.211	0.510	-0.332	0.466
$moved1$	-0.586	0.483	-0.706	0.499	0.591	0.432
$partners$	0.536 **	0.266	0.440	0.273	0.177	0.224
$managexp$	0.248	0.488	0.485	0.502	-0.054	0.452
$firequit$	0.332	0.514	0.246	0.526	-0.390	0.482
$diffprod$	-0.619	0.410	-0.464	0.423	0.247	0.373
$parenown$	0.065	0.384	0.262	0.399	-0.406	0.350
$educlev$	-0.037	0.114	-0.009	0.117	0.024	0.101
$opercont$	0.144	0.172	0.216	0.176	-0.304 *	0.157
$capinv$	0.098	0.125	0.030	0.128	0.128	0.111
$oddsyr$	0.116	0.092	0.138	0.094	-0.106	0.083
$agef$	0.003	0.028	0.007	0.029	0.030	0.026
$lgl - form1 - 2$	-0.531	0.643	-1.089 *	0.659	1.424 **	0.563
$lgl - form1 - 3$	0.078	0.455	-0.048	0.472	0.498	0.416
$homestead$					0.005	0.008
$h_unlimited$					-0.207	0.615
HH					0.000	0.000
$debt2assets$					0.644	0.955
$start1$					0.510 **	0.223
$Invest/Inside$	-0.090	0.180	1.728 ***	0.122		
$Sigma$			-38.625 ***	3.424		

Note: The sample size is 1,342; *** - significant at 1%, ** - significant at 5%.

Table A.12: Model II: Changemp - Outside/Inside

	Changemp		Changemp		Outside/Inside	
Parameter	Posterior Mean	Posterior Std.	Posterior Mean	Posterior Std.	Posterior Mean	Posterior Std.
$Intercept$	-0.323	1.398	-0.314	1.397	-4.544 **	1.915
$age1$	0.008	0.020	0.008	0.020	-0.047	0.030
$totjobs$	-0.021	0.047	-0.021	0.048	-0.045	0.075
$bs11$	0.010	0.011	0.009	0.011	-0.017	0.017
$bs21$	-0.009	0.010	-0.009	0.010	0.006	0.014
$bs61$	-0.012	0.016	-0.012	0.016	0.012	0.023
$race$	-0.563	0.750	-0.569	0.754	-0.927	1.101
$outjob4$	0.120	0.502	0.115	0.505	0.138	0.730
$unemp-change$	0.019	0.166	0.018	0.166		
$est-change$	0.775	1.786	0.768	1.781		
sex	-0.426	0.490	-0.427	0.490	0.408	0.708
$moved1$	-0.469	0.477	-0.475	0.480	-1.418 **	0.701
$partners$	0.537 **	0.262	0.537 **	0.262	0.312	0.369
$managexp$	0.431	0.483	0.431	0.486	-1.547 **	0.690
$firequit$	0.308	0.509	0.304	0.508	-0.155	0.749
$diffprod$	-0.605	0.407	-0.604	0.404	-0.145	0.588
$parenown$	0.057	0.381	0.060	0.384	-0.314	0.559
$educlev$	-0.047	0.112	-0.047	0.112	-0.017	0.162
$opercont$	0.116	0.169	0.115	0.168	0.020	0.244
$capinv$	0.048	0.123	0.047	0.125	1.387 ***	0.188
$oddsyr$	0.094	0.091	0.095	0.091	0.114	0.133
$agef$	0.001	0.028	0.001	0.028	0.023	0.042
$lgl-form1-2$	-0.856	0.637	-0.851	0.642	1.428	0.895
$lgl-form1-3$	0.094	0.451	0.097	0.451	-1.253 *	0.656
$homestead$					-0.007	0.021
$h_unlimited$					0.981	1.662
HH					-0.001 ***	0.000
$debt2assets$					0.946	2.177
$start1$					0.139	0.599
$Outside/Inside$	0.185 ***	0.035	0.183 ***	0.054		
$Sigma$			0.149	2.571		

Note: The sample size is 1,342; *** - significant at 1%, ** - significant at 5%.

Table A.13: Model III: Sales/Employee - Loans

	Sales/Employee		Sales/Employee		Loans	
Parameter	Posterior Mean	Posterior Std.	Posterior Mean	Posterior Std.	Posterior Mean	Posterior Std.
$Intercept$	-0.019	0.126	-0.147	0.161	-0.192	0.168
$age1$	0.000	0.002	0.002	0.002	-0.003	0.002
$totjobs$	-0.004	0.004	0.001	0.005	-0.007	0.005
$bs11$	-0.001	0.001	-0.001	0.001	0.001	0.001
$bs21$	0.000	0.001	-0.001	0.001	0.001	0.001
$bs61$	-0.001	0.001	-0.001	0.002	0.001	0.002
$race$	0.007	0.063	0.043	0.081	-0.072	0.083
$outjob4$	0.052	0.041	0.025	0.053	-0.001	0.054
$unemp-change$	0.022	0.014	0.000	0.010		
$est-change$	0.116	0.176	0.019	0.126		
sex	-0.019	0.040	-0.095 *	0.052	0.136 ***	0.052
$moved1$	-0.038	0.039	0.023	0.050	-0.033	0.051
$partners$	-0.005	0.021	0.011	0.027	-0.013	0.028
$managexp$	0.051	0.040	0.109 **	0.051	-0.075	0.051
$firequit$	-0.017	0.041	-0.022	0.053	0.010	0.054
$diffprod$	0.010	0.033	0.011	0.042	-0.033	0.043
$parenown$	-0.015	0.031	0.006	0.040	-0.019	0.040
$educlev$	-0.001	0.009	0.000	0.012	0.001	0.012
$opercont$	0.010	0.014	0.004	0.018	-0.011	0.018
$capinv$	0.019 *	0.010	-0.063 ***	0.013	0.100 ***	0.013
$oddsyr$	0.007	0.007	0.004	0.010	0.005	0.010
$agef$	-0.003	0.002	-0.006 **	0.003	0.005 *	0.003
$lgl-form1-2$	-0.028	0.052	0.016	0.067	-0.061	0.068
$lgl-form1-3$	-0.035	0.037	0.078	0.048	-0.117 **	0.049
$homestead$					0.000	0.001
$h_unlimited$					0.016	0.075
HH					0.000 *	0.000
$debt2assets$					-0.002	0.120
$start1$					-0.030	0.024
$Loans$	-0.057	0.049	1.387 ***	0.056		
$Sigma$			-0.430 ***	0.023		

Note: The sample size is 1,489; *** - significant at 1%, ** - significant at 5%.

Table A.14: Model III: Sales/Employee - Invest

	Sales/Employee		Sales/Employee		Invest	
Parameter	Posterior Mean	Posterior Std.	Posterior Mean	Posterior Std.	Posterior Mean	Posterior Std.
$Intercept$	-0.022	0.126	-0.121	0.130	-1.437 ***	0.487
$age1$	0.000	0.002	0.001	0.002	-0.003	0.006
$totjobs$	-0.003	0.004	-0.006	0.004	0.013	0.013
$bs11$	-0.001	0.001	-0.001	0.001	0.000	0.003
$bs21$	0.000	0.001	0.000	0.001	-0.001	0.003
$bs61$	-0.001	0.001	-0.001	0.001	0.003	0.004
$race$	0.008	0.063	0.033	0.065	-0.157	0.246
$outjob4$	0.051	0.041	0.060	0.043	-0.151	0.150
$unemp-change$	0.022 *	0.014	0.013	0.012		
$est-change$	0.129	0.175	0.057	0.150		
sex	-0.022	0.040	-0.013	0.042	-0.181	0.161
$moved1$	-0.035	0.039	-0.052	0.041	0.165	0.136
$partners$	-0.004	0.021	-0.029	0.022	0.229 ***	0.066
$managexp$	0.053	0.040	0.065	0.041	-0.030	0.151
$firequit$	-0.017	0.041	-0.022	0.043	-0.017	0.158
$diffprod$	0.010	0.033	0.028	0.035	-0.070	0.120
$parenown$	-0.015	0.031	0.004	0.032	-0.060	0.112
$educlev$	-0.001	0.009	0.001	0.009	-0.004	0.032
$opercont$	0.010	0.014	0.018	0.014	-0.082	0.050
$capinv$	0.017 *	0.010	0.007	0.010	0.060 *	0.036
$oddsyr$	0.007	0.007	0.010	0.008	-0.034	0.027
$agef$	-0.003	0.002	-0.003	0.002	0.018 **	0.008
$lgl-form1-2$	-0.025	0.052	-0.070	0.054	0.274	0.176
$lgl-form1-3$	-0.030	0.037	-0.057	0.038	0.277 **	0.133
$homestead$					0.002	0.004
$h_{u}nlimited$					-0.201	0.301
HH					0.000	0.000
$debt2assets$					0.265	0.475
$start1$					0.151	0.108
$Invest$	-0.025	0.109	1.148 ***	0.077		
$Sigma$			-0.636 ***	0.068		

Note: The sample size is 1,489; *** - significant at 1%, ** - significant at 5%.

Table A.15: Model III: Sales/Employee - Outside

	Sales/Employee		Sales/Employee		Outside	
Parameter	Posterior Mean	Posterior Std.	Posterior Mean	Posterior Std.	Posterior Mean	Posterior Std.
$Intercept$	-0.013	0.126	-0.269	0.165	-0.056	0.155
$age1$	0.000	0.002	0.003	0.002	-0.004 *	0.002
$totjobs$	-0.004	0.004	-0.002	0.005	-0.002	0.005
$bs11$	-0.001	0.001	-0.001	0.001	0.000	0.001
$bs21$	0.000	0.001	-0.001	0.001	0.001	0.001
$bs61$	-0.001	0.001	-0.002	0.002	0.001	0.002
$race$	0.005	0.063	0.075	0.084	-0.088	0.077
$outjob4$	0.052	0.042	0.034	0.055	-0.016	0.051
$unemp-change$	0.022	0.014	0.001	0.010		
$est-change$	0.116	0.175	0.030	0.119		
sex	-0.020	0.040	-0.087	0.053	0.109 **	0.049
$moved1$	-0.037	0.039	0.005	0.052	-0.004	0.047
$partners$	-0.003	0.021	-0.020	0.028	0.025	0.026
$managexp$	0.050	0.040	0.123 **	0.052	-0.073	0.048
$firequit$	-0.017	0.041	-0.026	0.055	0.011	0.051
$diffprod$	0.010	0.033	0.033	0.044	-0.044	0.040
$parenown$	-0.016	0.031	0.028	0.041	-0.042	0.038
$educlev$	-0.001	0.009	0.002	0.012	-0.001	0.011
$opercont$	0.010	0.014	0.015	0.018	-0.022	0.017
$capinv$	0.020 *	0.011	-0.077 ***	0.014	0.102 ***	0.012
$oddsyr$	0.007	0.008	0.008	0.010	0.001	0.009
$agef$	-0.003	0.002	-0.006 **	0.003	0.005 *	0.003
$lgl-form1-2$	-0.027	0.052	-0.036	0.069	0.008	0.064
$lgl-form1-3$	-0.033	0.037	0.048	0.049	-0.064	0.045
$homestead$					0.000	0.001
$h_unlimited$					-0.006	0.065
HH					0.000 *	0.000
$debt2assets$					-0.022	0.104
$start1$					-0.017	0.021
$Outside$	-0.059	0.048	1.451 ***	0.056		
$Sigma$			-0.425 ***	0.022		

Note: The sample size is 1,489; *** - significant at 1%, ** - significant at 5%.

Table A.16: Model III: Sales/Employee - Loans/Inside

	Sales/Employee		Sales/Employee		Loans	
Parameter	Posterior Mean	Posterior Std.	Posterior Mean	Posterior Std.	Posterior Mean	Posterior Std.
$Intercept$	-0.026	0.126	-0.053	0.139	-2.822	1.809
$age1$	0.000	0.002	0.002	0.002	-0.047 *	0.028
$totjobs$	-0.003	0.004	-0.002	0.005	-0.066	0.069
$bs11$	-0.001	0.001	0.000	0.001	0.000	0.016
$bs21$	0.000	0.001	-0.001	0.001	0.015	0.013
$bs61$	-0.001	0.001	-0.001	0.002	0.010	0.022
$race$	0.008	0.063	0.030	0.075	-0.853	1.035
$outjob4$	0.051	0.042	0.044	0.050	-0.135	0.694
$unemp-change$	0.022	0.014	-0.001	0.010		
$est-change$	0.129	0.174	-0.090	0.126		
sex	-0.022	0.041	-0.032	0.049	1.201 *	0.670
$moved1$	-0.037	0.039	0.021	0.048	-0.672	0.657
$partners$	-0.004	0.021	0.001	0.026	-0.107	0.362
$managexp$	0.052	0.040	0.121 **	0.048	-1.415 **	0.658
$firequit$	-0.017	0.041	-0.022	0.051	0.146	0.701
$diffprod$	0.011	0.033	0.010	0.040	-0.398	0.557
$parenown$	-0.014	0.031	-0.026	0.038	0.115	0.525
$educlev$	0.000	0.009	-0.003	0.011	0.055	0.153
$opercont$	0.010	0.014	-0.004	0.017	0.001	0.232
$capinv$	0.017 *	0.010	-0.003	0.012	0.811 ***	0.173
$oddsyr$	0.007	0.008	0.000	0.009	0.130	0.125
$agef$	-0.003	0.002	-0.004	0.003	0.053	0.039
$lgl-form1-2$	-0.024	0.053	-0.122 *	0.063	0.976	0.864
$lgl-form1-3$	-0.031	0.037	-0.009	0.045	-0.802	0.626
$homestead$					0.000	0.012
$h_unlimited$					0.247	0.986
HH					-0.001 **	0.000
$debt2assets$					-0.256	1.453
$start1$					-0.341	0.323
$Loans/Inside$	-0.002	0.003	0.075 ***	0.004		
$Sigma$			-5.386 ***	0.265		

Note: The sample size is 1,310; *** - significant at 1%, ** - significant at 5%.

Table A.17: Model III: Sales/Employee - Invest/Inside

	Sales/Employee		Sales/Employee		Invest/Inside	
Parameter	Posterior Mean	Posterior Std.	Posterior Mean	Posterior Std.	Posterior Mean	Posterior Std.
$Intercept$	-0.022	0.126	-0.169	0.125	-4.220 **	1.707
$age1$	0.000	0.002	0.002	0.002	-0.030	0.027
$totjobs$	-0.003	0.004	-0.004	0.004	0.068	0.056
$bs11$	-0.001	0.001	-0.001	0.001	0.000	0.015
$bs21$	0.000	0.001	0.000	0.001	-0.011	0.012
$bs61$	-0.001	0.001	0.000	0.001	0.014	0.019
$race$	0.009	0.063	0.030	0.065	-0.956	1.038
$outjob4$	0.051	0.041	0.057	0.043	-0.821	0.639
$unemp - change$	0.022 *	0.014	0.015	0.012		
$est - change$	0.130	0.175	0.047	0.147		
sex	-0.023	0.040	-0.005	0.041	-0.830	0.684
$moved1$	-0.035	0.039	-0.046	0.040	0.786	0.584
$partners$	-0.004	0.021	-0.011	0.022	1.033 ***	0.294
$managexp$	0.053	0.040	0.077 *	0.041	-0.415	0.639
$firequit$	-0.017	0.042	-0.023	0.043	-0.086	0.673
$diffprod$	0.010	0.033	0.023	0.034	-0.507	0.518
$parenown$	-0.015	0.031	0.005	0.032	-0.496	0.492
$educlev$	-0.001	0.009	0.003	0.009	-0.062	0.139
$opercont$	0.010	0.014	0.017	0.014	-0.494 **	0.224
$capinv$	0.016	0.010	0.011	0.010	0.315 **	0.159
$oddsyr$	0.007	0.008	0.011	0.008	-0.203 *	0.115
$agef$	-0.003	0.002	-0.003	0.002	0.065 *	0.035
$lgl - form1 - 2$	-0.025	0.052	-0.062	0.054	1.645 **	0.748
$lgl - form1 - 3$	-0.030	0.037	-0.040	0.038	1.360 **	0.577
$homestead$					0.005	0.015
$h_unlimited$					-0.416	1.246
HH					0.000	0.000
$debt2assets$					0.906	1.761
$start1$					0.784 *	0.460
$Invest/Outside$	-0.002	0.015	0.142 ***	0.012		
$Sigma$			-2.789 ***	0.272		

Note: The sample size is 1,310; *** - significant at 1%, ** - significant at 5%.

Table A.18: Model III: Sales/Employee - Outside/Inside

	Sales/Employee		Sales/Employee		Outside/Inside	
Parameter	Posterior Mean	Posterior Std.	Posterior Mean	Posterior Std.	Posterior Mean	Posterior Std.
Intercept	-0.024	0.126	-0.078	0.146	-1.902	1.700
*age*1	0.000	0.002	0.002	0.002	-0.049 *	0.026
totjobs	-0.003	0.004	-0.003	0.005	-0.018	0.062
*bs*11	-0.001	0.001	0.000	0.001	0.001	0.015
*bs*21	0.000	0.001	-0.001	0.001	0.012	0.012
*bs*61	-0.001	0.001	-0.001	0.002	0.013	0.020
race	0.007	0.063	0.043	0.079	-0.923	0.957
*outjob*4	0.051	0.041	0.042	0.053	-0.227	0.640
$unemp - change$	0.022 *	0.014	-0.001	0.010		
$est - change$	0.130	0.174	-0.073	0.117		
sex	-0.023	0.040	-0.027	0.052	0.866	0.624
*moved*1	-0.037	0.039	0.022	0.050	-0.379	0.606
partners	-0.004	0.021	-0.003	0.027	0.167	0.329
managexp	0.051	0.040	0.140 ***	0.051	-1.393 **	0.614
firequit	-0.017	0.041	-0.028	0.053	0.182	0.648
diffprod	0.011	0.033	0.015	0.043	-0.419	0.516
parenown	-0.015	0.031	-0.018	0.040	-0.094	0.484
educlev	-0.001	0.009	-0.003	0.012	0.043	0.142
opercont	0.010	0.014	-0.004	0.018	-0.063	0.214
capinv	0.017 *	0.010	-0.009	0.013	0.755 ***	0.159
oddsyr	0.007	0.008	-0.001	0.010	0.107	0.115
agef	-0.003	0.002	-0.005	0.003	0.053	0.036
$lgl - form1 - 2$	-0.023	0.052	-0.156 **	0.066	1.631 **	0.793
$lgl - form1 - 3$	-0.031	0.037	-0.013	0.048	-0.316	0.577
homestead					0.004	0.010
$h_u nlimited$					-0.013	0.816
HH					0.000 **	0.000
debt2assets					-0.172	1.250
*start*1					-0.122	0.270
Outside/Inside	-0.002	0.003	0.084 ***	0.004		
Sigma			-5.464 ***	0.252		

Note: The sample size is 1,310; *** - significant at 1%, ** - significant at 5%.

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